

**Eurochambres Chief Economists  
Working Paper #3**

# **The effects of AI on Europe's productivity**



## Foreword

Rarely has a technology generated as much excitement, investment and expectation in such a short period of time as artificial intelligence. Yet for many European businesses, the reality remains less clear: where exactly does AI create value, and how can that value be translated into higher productivity and growth? This study seeks to shed light on these questions by examining how AI is being adopted across Europe and whether these adoption patterns are already associated with measurable economic outcomes.

This question is especially important at a time when Europe urgently needs new sources of productivity growth. While AI offers considerable promise, its economic benefits will not materialise automatically. Whether AI translates into higher productivity will depend on how widely and effectively it is adopted across businesses, sectors and regions.

This study makes a valuable contribution to understanding that process. Its findings show that AI adoption among European companies is increasing, while also revealing persistent differences between countries, sectors and firm sizes. The analysis provides encouraging evidence of a positive association between AI adoption and labour productivity, particularly in areas such as image recognition, process automation, and marketing and sales. At the same time, the findings remind us that technology alone is not sufficient. Skills, investment, data, infrastructure and organisational change are all essential to translate adoption into measurable gains.

The challenge is therefore not only to raise awareness of AI, but to broaden its diffusion and support its effective implementation. This is especially important for SMEs, which form the backbone of Europe's economy but consistently lag behind larger companies in AI adoption. Unless this gap is addressed, the benefits of AI risk remaining concentrated among those businesses already best equipped to seize them.

Chambers of commerce and industry have a unique role to play. Their proximity to companies allows them to turn technological potential into practical results by helping businesses identify relevant use cases, build skills and move from experimentation to implementation. The examples collected in this report show that chambers across Europe are already doing precisely this.

The true test of Europe's AI transition will be whether businesses across all sectors, regions and sizes can translate technological advances into tangible improvements in productivity and growth. This requires a sustained focus on adoption and implementation, supported by a policy environment that enables European businesses to invest, innovate and remain competitive.

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## **Abstract**

*Over the past few years, artificial intelligence (AI) has moved to the centre of global economic attention, but its economic impacts, especially on European businesses, are yet to be clearly understood. In this paper, we examine AI adoption across European countries and investigate its relationship with labour productivity. We find that, despite an overall average increase in AI adoption in Europe in 2021-2025, substantial heterogeneity remains across countries, sectors and firm sizes, with clear evidence of small and medium-sized enterprises (SMEs) lagging behind in AI adoption – a finding universal to all countries considered. Using a fixed-effects regression framework, we find evidence of a positive and significant relationship between AI adoption and labour productivity, pointing to (i) AI-based image recognition and (ii) AI-based process automation as the technologies most significantly linked with higher labour productivity, and marketing and sales as the area in which labour productivity increase is most visible. We finally compile best practices from European chambers of commerce and industry, and provide policy recommendations to strengthen AI adoption by European companies.*

## **Acknowledgments**

This report is the result of a joint effort of the Eurochambres Chief Economists Group. Eurochambres would like to extend its gratitude in particular to the Hungarian Chamber of Commerce and Industry and to its research team, as well as to Professor Laszlo Trautmann, Head of Research at MKIK-GVI and Associate Professor at John von Neumann University; Benedek Lits, Doctorate Student and Researcher at Corvinus University of Budapest; and Budai Júlia Dorka, Msc Student at Vienna University of Economics and Business, for their analytical contribution to this work. Eurochambres also gratefully acknowledges the contributions of the German Chamber of Commerce and Industry (DIHK), the Austrian Federal Economic Chamber (WKO), the Chamber of Commerce Luxembourg, Brussels Chamber of Commerce (BECI), the Chamber of Commerce of Spain, Unioncamere and Research Center Istituto Guglielmo Tagliacarne, the Chamber of Commerce and Industry of Slovenia (GZS), as well as the valuable work of the members of Eurochambres' Digital Working Group.

## **Disclaimers**

*The following working paper has been produced by the Eurochambres Chief Economists Group for research and discussion purposes. It should not be considered as an official Eurochambres position.*

*This paper was prepared with the support of artificial intelligence (AI).*

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## 1. Introduction

Over the past few years, artificial intelligence (AI) has moved from being a niche technological field to the centre of global economic attention. Investment, expectations, and public discourse have reached unprecedented levels, driven by rapid advances in model capabilities and widespread anticipation of transformative economic effects. Yet, as with previous technological waves, the current moment is characterised by a tension between hype and measurable impact.

On the one hand, the scale of investment signals a structural shift. The largest technology companies are committing vast resources to AI development and deployment, with spending reaching levels that are macroeconomically significant. In 2026 alone, a few hyperscalers are expected to invest around **\$725 billion or more** in capital expenditure—Amazon (~\$200bn), Microsoft (~\$190bn), Alphabet (~\$175–185bn), and Meta (~\$115–135bn).<sup>1</sup> Taken together, this is several times larger than the **EU's annual budget of roughly €190 billion**. At the same time, global AI spending is projected to rise further, reaching **over \$3 trillion by 2027**<sup>2</sup>, underlining the growing strategic importance of the technology across sectors and countries. These developments have fuelled expectations that AI could constitute a general-purpose technology with effects comparable to past industrial revolutions.

On the other hand, current dynamics also resemble earlier periods of technological exuberance. The evolution of AI capabilities follows a familiar pattern: rapid progress drives inflated expectations, followed by phases of adjustment as practical limitations and adoption barriers become apparent. While model performance has improved significantly and continues to accelerate, the translation of these technological advances into broad-based productivity gains remains uneven. Many companies are still experimenting with AI through pilot projects rather than fully integrating it into core business processes, and adoption across the broader economy remains incomplete.

A key feature of the current AI wave is the simultaneous acceleration of capabilities and reduction in costs. Advances in model architectures, training techniques, and hardware have led to rapid improvements in performance benchmarks, while the cost of deploying comparable AI capabilities has declined sharply. This combination has lowered barriers to entry and increased the potential for diffusion, suggesting that AI could become ubiquitous across a wide range of economic activities. At the same time, frontier development remains highly capital-intensive, with substantial investment required in compute infrastructure, data, and talent.

These trends raise fundamental questions for both policymakers and businesses. Is the current AI boom indicative of a sustained technological transformation with strong productivity effects, or does it risk overshooting economic fundamentals, as seen during the dot-com era? At the same time, innovation is not neutral in its effects: without the right social and economic embedding, it can amplify existing imbalances rather than resolve them, rather than supporting human dignity and broadly shared progress. This insight is

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<sup>1</sup> <https://finance.yahoo.com/sectors/technology/article/meta-microsoft-amazon-and-alphabet-are-about-to-spend-a-shocking-amount-of-money-to-dominate-the-ai-era-115359575.html?guccounter=1>

<sup>2</sup> <https://www.gartner.com/en/newsroom/press-releases/2026-1-15-gartner-says-worldwide-ai-spending-will-total-2-point-5-trillion-dollars-in-2026>

particularly relevant in the current AI transition, where unprecedented investment and capability growth coexist with uneven adoption and uncertain productivity outcomes.

From a European perspective, these questions are especially salient. The global AI landscape is increasingly shaped by large-scale investments and technological leadership in the United States. At the same time, structural characteristics of the European economy—including lower levels of digital investment, fragmentation of capital markets, and slower technology adoption—may hinder the region’s ability to fully capture the productivity gains associated with AI.

In an extreme scenario, this dependence could move beyond abstract concerns about “technological sovereignty” and translate into concrete vulnerabilities: if critical technologies, platforms, or models are withdrawn, restricted, or reprioritised outside Europe, entire value chains could be disrupted. Recent debates around the withdrawal of key platforms and the inaccessibility of proprietary systems (e.g., Anthropic’s ‘Fable’ and ‘Mythos’) highlight how technological dependence can quickly translate into strategic vulnerabilities—affecting competitiveness, security, and the EU’s ability to control critical digital infrastructure.

This raises concerns about widening competitiveness gaps and reinforces the importance of policies aimed at accelerating AI diffusion, particularly among small and medium-sized enterprises. The challenge for Europe is therefore not only to participate in the AI race, but to ensure that access to, and control over, critical technologies does not become a bottleneck for its economic model as a whole.

Against this backdrop, this study examines the relationship between AI adoption and economic outcomes in Europe, with a particular focus on labour productivity. It combines insights from the existing literature with new empirical evidence to assess whether current diffusion patterns are already translating into measurable economic effects. In doing so, it seeks to move beyond the prevailing narratives of both technological optimism and scepticism, providing instead an evidence-based assessment of where the European economy stands in the AI transition and what can be expected in the years ahead. The rest of the paper is structured as follows: 2. gives an overview of the pertinent literature on AI in the context of labour economics; 3. Details the empirical approach and results; 4. Introduces best practices from European chambers on how to help SMEs adopt AI; 5. Derives policy recommendations.

## **2. Literature review**

The scientific debate on how technology affects productivity and the labour market has been extensively examined in the labour economics literature. Researchers have studied how technological change affects productivity and labour markets since the Industrial Revolution (Mantoux, 1928). Theoretically, the emergence of new technologies, such as artificial intelligence, can increase productivity through several distinct channels (Acemoglu, 2024). Building on the task-based framework developed by Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018, 2019, 2022), AI is best understood as a technology that affects the production of individual tasks rather than entire occupations. First, AI can generate productivity gains through **automation**, whereby machines or algorithms perform tasks previously carried out by human labour, reducing production costs and increasing efficiency. Second, AI can operate through **task complementarities**, improving the

productivity of workers in tasks that are not fully automated. For example, AI systems may automate subtasks, provide decision support, or improve access to information, thereby enabling workers to specialise in higher-value activities. Third, AI may contribute to productivity growth through the **creation of new tasks**, products, and organisational processes that expand the production frontier and generate new forms of labour demand. While automation has dominated both public and academic discussions, the long-run effects of technological change on productivity and employment depend on the balance between displacement through automation and the emergence of new productive tasks (Acemoglu & Restrepo, 2018; Autor et al., 2024).

Empirically, several studies have shown that AI can increase productivity through a combination of **automation** and **augmentation**. Peng et al. (2023) show that access to GitHub Copilot enabled software developers to complete programming tasks approximately 56% faster, suggesting that AI can automate routine coding subtasks while allowing workers to focus on higher-level problem solving. Noy and Zhang (2023) find that ChatGPT reduced the time required to complete writing tasks by around 40% while simultaneously improving output quality, with the largest gains accruing to less experienced workers. Brynjolfsson et al. (2023) report that generative AI increased customer-service productivity by approximately 14% and helped novice workers reach the performance level of experienced colleagues more rapidly. These findings are broadly consistent with recent reviews suggesting that AI's productivity effects are currently strongest in service-sector and knowledge-intensive tasks, while manufacturing gains depend more heavily on integration with robotics, data infrastructure, process redesign and complementary investments (Filippucci et al., 2025).

The task-based literature suggests that the productivity effects of AI are unlikely to be uniform across firms, industries, or occupations. While the studies discussed above demonstrate substantial productivity gains for specific tasks, the firm-level effects of AI adoption depend on the extent to which workers and firms can identify tasks that can either be automated or augmented by AI. Consequently, task-level productivity improvements do not automatically translate into economy-wide productivity gains. Their overall impact will depend on the share of economically relevant tasks affected, the magnitude of productivity improvements within those tasks, and the speed with which AI is adopted and integrated into production processes (Acemoglu, 2024).

Recent studies have therefore sought to estimate whether such task-level gains translate into broader productivity effects, although their conclusions differ considerably depending on assumptions about AI exposure, adoption and complementarity. Acemoglu (2024) provides one of the more cautious estimates. He argues that aggregate productivity gains depend on the share of tasks affected by AI and the average cost savings associated with those tasks, estimating that AI would increase total factor productivity (TFP) by no more than 0.71% over ten years, and by less than 0.55% under more conservative assumptions in the US. By contrast, Aghion and Bunel (2024) arrive at more optimistic estimates: drawing on historical analogies with earlier technological revolutions, they estimate that AI could raise aggregate productivity growth by between 0.8 and 1.3 percentage points per year over the next decade, while their task-based recalibration yields a median estimate of 0.68 percentage points of additional annual TFP growth. The IMF's April 2024 World Economic Outlook estimates that AI could raise global productivity growth by between **0.1 and 0.8 percentage points annually over a decade**, depending on the extent of adoption and whether AI primarily replaces or augments workers.

For the euro area, Bergeaud (2024) adapts Acemoglu's framework and estimates TFP gains of 2.9% over the next ten years, equivalent to an additional 0.29 percentage points per year, with alternative scenarios ranging from 1.3% to 4.5% over the same period. Importantly, recent evidence suggests that aggregate productivity gains from AI are unlikely to be distributed evenly across countries. Using data covering 56 economies and 16 industries, Gambacorta et al. (2025) show that the growth effects of generative AI depend not only on sectoral exposure but also on countries' technological readiness, including digital infrastructure, human capital, innovation capacity and regulatory frameworks. They find that sectors with high AI exposure experience faster growth in countries that are better prepared to adopt AI, while countries with production structures concentrated in knowledge-intensive and cognitively demanding sectors benefit more than those specialised in labour-intensive activities. As a result, the authors conclude that advanced economies are likely to experience larger short-run growth gains from AI than emerging economies, potentially widening existing cross-country productivity and income gaps.

Aldasoro et al. (2026) address a key challenge in estimating the productivity effects of AI: firms that adopt AI are typically already more productive, larger, and more innovative than non-adopters. To isolate the causal effect of AI adoption, the authors construct an instrumental-variable strategy based on matched US firms. Specifically, each European firm is matched to similar US firms according to characteristics such as sector, size, investment intensity, innovation activity and management practices. The AI adoption rate among these comparable US firms is then used as an instrument for AI adoption by the European firm, under the assumption that it predicts AI adoption but does not directly affect the firm's productivity. Using this approach, the authors find that AI adoption increases labour productivity by around 4%. They further show that these gains are driven primarily by capital deepening and complementary investments rather than reductions in employment, suggesting that AI mainly augments workers rather than replacing them in the short run. Productivity gains are concentrated among medium-sized and large firms and are strongest when AI adoption is accompanied by investments in software, data infrastructure and workforce training.

From a policy and business perspective, an important insight is that technology adoption alone is not sufficient to ensure productivity gains. Drawing on the experience of previous general-purpose technologies, Baily, Brynjolfsson and Korinek (2023) argue that realizing the productivity benefits of generative AI requires substantial complementary investments in intangible assets, including worker skills, organisational capabilities and business process redesign. They emphasize that, as with earlier digital technologies, productivity gains may materialise only gradually as firms adapt their organisational structures and integrate AI into core business functions. For, this suggests that competitive advantages are likely to depend not only on AI adoption alone, but also on the ability to make the complementary investments necessary to translate technological capabilities into productivity gains.

### **3. Empirical research**

After examining the literature findings, we set out to perform the empirical analysis, looking at the distribution of AI adoption in Europe and investigating its impact on labour productivity.

### 3.1 Data

The main data source for the empirical analysis is the Eurostat ICT usage in enterprises survey (2026), which includes annual aggregates of AI adoption rates among European firms for the years 2021, 2023, 2024, and 2025. The countries considered include the EU27 Member States plus Norway, Albania, Bosnia and Herzegovina, Montenegro and Serbia. Our main variable – AI adoption – was constructed using the indicator E\_AI\_TANY (referred to as TANY hereafter), which captures the share of companies with ten or more employees using at least one AI technology. We also included two sets of sub-indicators: (i) AI technologies used and (ii) purposes for which AI is used. Other subindicators were excluded due to lack of reliability or due to being out of the scope of this analysis. The data was then analysed across different levels of disaggregation. The first dataset examined observations of AI adoption and at the two sub-indicators by country, economic sector and year (country  $\times$  sector  $\times$  year). The second dataset examined AI adoption across firm sizes (small, medium, large) using country  $\times$  sector  $\times$  size  $\times$  year cells, with limited sector variance.

In addition to Eurostat, we used firm-level financial data from Orbis database (Bureau van Dijk, 2026). Unlike Eurostat, which only provides *averages* for groups of firms, Orbis contains information on individual companies. We used data for the years 2020-2024 (2025 is excluded as some firms had not yet reported their financial statements).

We then constructed the firm characteristics (firm age, firm size, sector) and control variables used in the empirical analysis (investment, leverage, logarithm of total assets). We classified firms into four age groups (startup: under 10 years; young: 10-19; mature: 20-39; and old: 40 or more) and used employee headcount data to assign each firm-year observation to a size class (small: 10-49 employees; medium: 50-249; large: 250 or more). Orbis also provides detailed information on each company's sector (identified with a NACE code e.g., C10.11), which was mapped onto Eurostat broader industry group classification (e.g., C10-12) to enable the merging of the two datasets<sup>3</sup>. Investment was calculated as  $I(t) = TFA(t) - TFA(t-1) + DA(t)$ , where TFA is tangible fixed assets, and DA is depreciation and amortisation. Leverage was instead defined as the ratio of short-term debt to total assets, and the natural logarithm of total assets was included as control for firm scale.

Since Eurostat ICT survey provides the AI adoption rates only for aggregated groups of firms rather than individual companies, we merged the Eurostat data with firm-level observations from Orbis. We matched each firm-year observation in Orbis to the corresponding country  $\times$  sector  $\times$  year AI adoption rate reported by Eurostat. AI adoption therefore enters the regression as an externally constructed regressor, rather than as a direct measure of firm-level AI adoption. The resulting merged dataset combines firm-level financial information with AI adoption rates measured at the aggregate country  $\times$  sector  $\times$  year level. Each financial observation is identified by its country, sector, size class, age group and year.

### 3.2 Descriptive results

This section presents descriptive evidence on AI adoption across European countries, firm sizes and economic sectors. These patterns provide the empirical context for the regression analysis that follows.

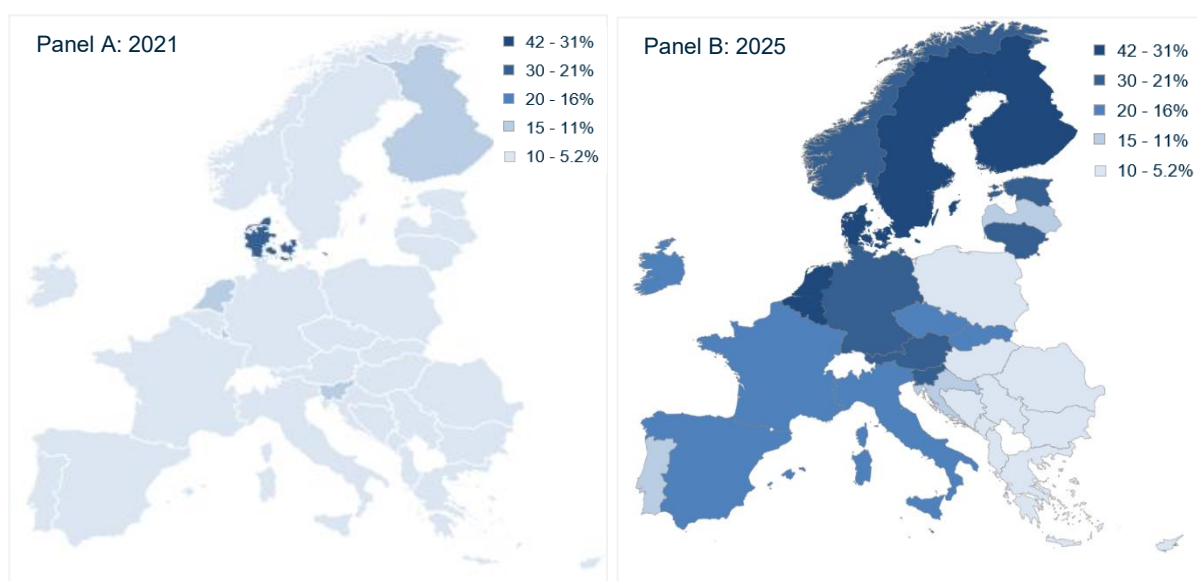
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<sup>3</sup> Eurostat ICT survey data only reports AI adoption for broader industry groups (e.g., C10-12), not for specific sectors. Overall, we included 31 sectors. More information is included in Annex 7.1.

## AI adoption across European countries

Figure 1 presents the geographical distribution of AI adoption (measured as TANY) across 32 European countries (EU27 plus Norway, Albania, Bosnia and Herzegovina, Montenegro and Serbia) in 2021 and 2025. Overall, it shows a general increase in AI adoption in Europe between 2021 and 2025. In 2021, most countries exhibited either low (10-15%) or very low (less than 10%) rates of AI adoption, with an EU average standing at 7.65%. By 2025, the latter had increased to 19.95%. Denmark is a notable exception, with an AI adoption rate in 2021 (23.89%) considerably higher than the EU average.

**Figure 1. AI adoption across European countries**



Data: TANY 2021 and 2025, Eurostat, authors' own calculations.

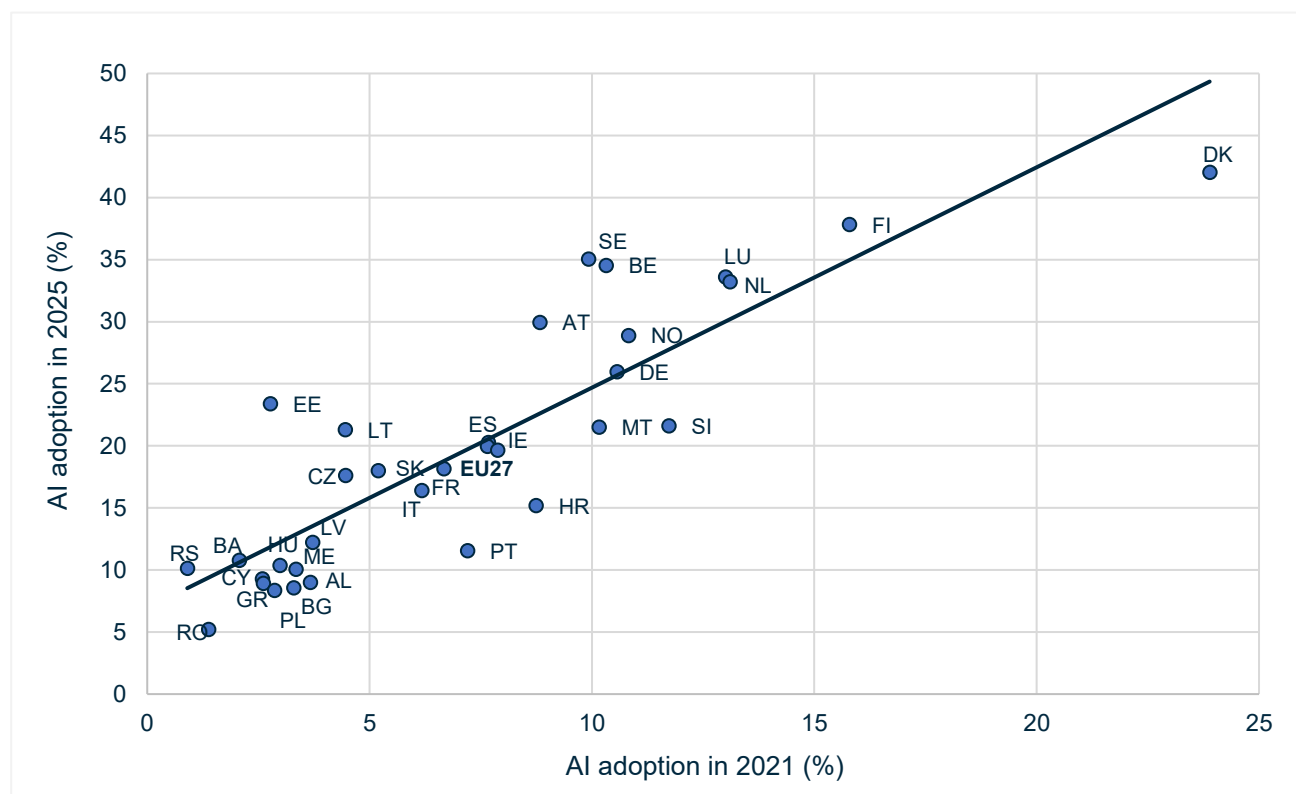
The map of national AI adoption rates in 2025 shows a significantly more heterogeneous pattern of adoption, making the clear geographical divide immediately visible. A Nordic-led cluster, Finland, Sweden, Denmark, and the Benelux, occupies the top band (31-42%), adopting AI at almost twice the EU average (19.95%), while a contiguous Eastern and Southeastern bloc spanning Poland, Hungary, Romania, Bulgaria, and Greece sits in the lowest band (5.2-10%) of AI adoption rates. The continental economies cluster around the middle of the distribution.

Figure 2 plots national adoption rates in 2025 against those in 2021. The strong positive relationship between initial and final adoption rates ( $R^2 = 0.75$ ) indicates that countries with relatively high AI adoption in 2021 generally remained among the highest adopters in 2025. This suggests that differences in AI adoption across countries persisted over time, with limited evidence of convergence between early and late adopters. The Nordic economies, led by Finland and Denmark, sit at the adoption frontier in both years, while several Southern and Eastern European countries remain at the lower end of the distribution.

A few countries deviate from the general trend. Estonia and Sweden for example, record a higher AI adoption rate in 2025 than would be expected based on their initial position, indicating faster AI adoption over the considered period. On the other hand, countries below

the line experienced slower rates of adoption than expected. These differences suggest that country-specific characteristics influence the pace at which firms adopt AI and contribute to creating an overall heterogeneous outlook.

**Figure 2. AI-adoption rates in 2021 and 2025 by country.**



Data: TANY 2021 and 2025, Eurostat, authors' own calculations.

These results show a general trend of increased AI adoption in Europe over the considered period. Nevertheless, the pattern is clearly uneven and likely reflects national differences in economic composition, digital infrastructure, innovation capacity, availability of skilled personnel or institutional conditions that facilitate technology adoption.

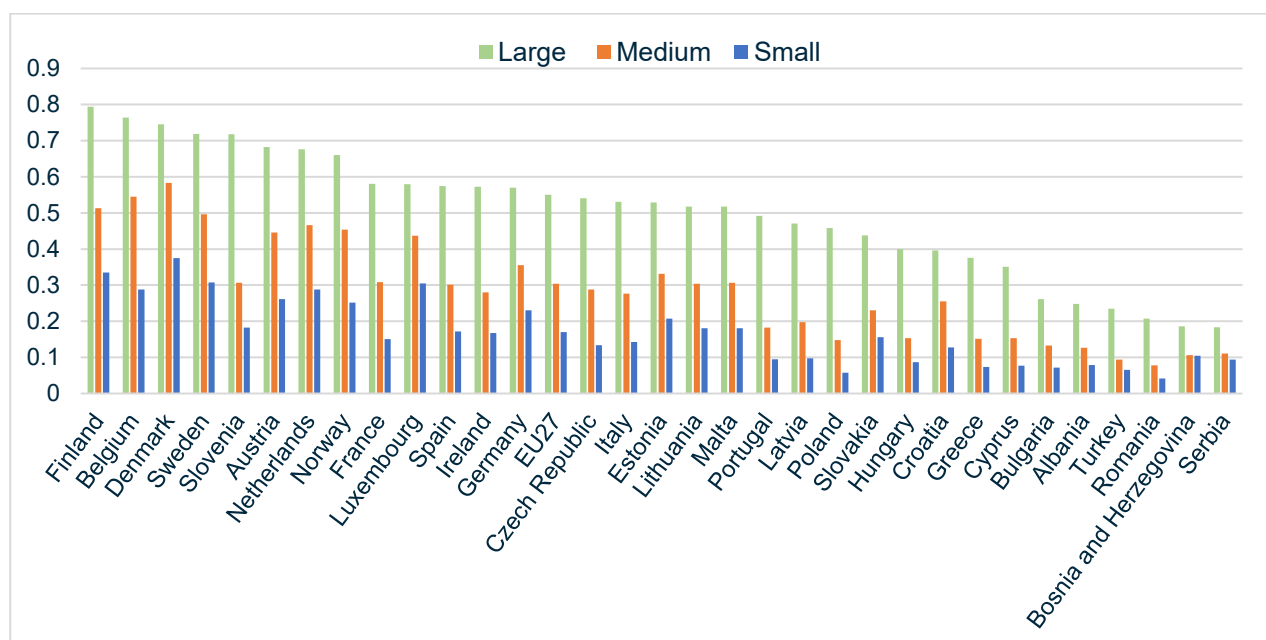
## AI adoption across firm sizes

Figure 3 disaggregates 2025 AI adoption in European countries according to firm size. We distinguish between small (10-49 employees), medium (50-249), and large (250 or more) enterprises within the non-financial economy<sup>4</sup>. The graph reveals a consistent firm-size gradient: in every considered economy, large firms adopt AI at substantially higher rates than medium firms, which in turn show higher adoption rates than small firms. The gradient is steep and near universal, holding across countries at every point in the overall adoption distribution. This pattern of adoption rising monotonically with firm size is among the most robust regularities in the descriptive data.

The pattern is theoretically intuitive, as larger firms are likely to possess larger financial resources, technical expertise, and organisational capabilities than small and medium-sized enterprises (SMEs), thus being better able to sustain the costs associated with AI adoption.

<sup>4</sup> We consider sectors C10-S951 in Eurostat and exclude K, i.e., the financial sector.

**Figure 3. AI-adoption in 2025 by firm size and country, 2025**



Data: Eurostat, authors' own calculations.

This is in line with the literature findings showing that productivity gains accrue mostly to larger and medium-sized firms, while depending critically on complementary investments (Aldasoro et al., 2026). While SMEs may require additional support to overcome adoption barriers, the experience of Nordic countries illustrates that smaller firms can achieve relatively high AI adoption rates under favourable institutional and business conditions.

### AI adoption across economic sectors

Figure 4 presents a heat map of 2025 AI adoption rates across the intersection of country and broad sector grouping. The map includes data for the 10 European countries with the highest rate of AI adoption in 2025. *Information and communication technologies* as well as *professional, scientific, and technical* activities consistently display the darkest shading across considered countries, indicating that knowledge-intensive service sectors exhibit the highest AI adoption, irrespective of national context<sup>5</sup>. At the other extreme, *construction, wholesale and retail trade* and, for some countries, segments of *manufacturing*, record the lightest shading, reflecting persistently low uptake. Reading across rows, the Nordic countries exhibit high adoption across nearly all sectors, whereas in lower-ranked countries, elevated adoption is confined to a narrow set of leading sectors.

Belgium records exceptionally high AI adoption rates in the energy supply sector (90% companies), while Finland displays the overall highest adoption rate in the ICT sector, reflecting the industrial structure of its national economy. The relatively high AI adoption observed in Belgium's energy sector is consistent with evidence of advanced AI deployment by major Belgian energy-sector actors. Elia Group, for example, has been implementing AI and machine-learning applications for forecasting, predictive maintenance, incident detection and operational optimisation already since 2020 (Jones, 2024). More broadly, the

<sup>5</sup> An analysis performed on a larger sample of 33 European countries (EU27 plus Albania, Bosnia and Herzegovina, Montenegro, Serbia, Turkey and Norway) showed that *ICT* and *professional, scientific and technical activities* consistently ranked in the top 3 sectors with the highest AI adoption rate across all countries (see Annex 7.2).

Figure 4. AI adoption rate by country and sector, 2025

|               | Information & Communication | Professional, Scientific & Technical | Manufacturing | Energy Supply | Wholesale & Retail Trade | Construction |
|---------------|-----------------------------|--------------------------------------|---------------|---------------|--------------------------|--------------|
| Belgium       | 80%                         |                                      | 76%           | 90%           | 31%                      | 19%          |
| Denmark       | 78%                         | 61%                                  | 37%           |               | 40%                      | 23%          |
| Netherlands   | 66%                         | 57%                                  | 31%           | 55%           | 27%                      | 21%          |
| Sweden        | 55%                         | 66%                                  | 40%           | 53%           | 29%                      | 7%           |
| Austria       | 80%                         | 51%                                  | 31%           |               | 25%                      | 14%          |
| Luxembourg    | 70%                         | 50%                                  | 25%           |               | 29%                      | 24%          |
| Germany       | 71%                         | 54%                                  | 29%           | 37%           | 25%                      | 14%          |
| Finland       | 82%                         |                                      | 21%           |               | 27%                      | 24%          |
| Slovenia      | 63%                         | 32%                                  | 27%           | 76%           | 27%                      | 5%           |
| Estonia       | 55%                         | 58%                                  | 30%           | 25%           | 16%                      | 17%          |
| EU-27 Average | 60%                         | 46%                                  | 23%           | 34%           | 18%                      | 11%          |

Data: Eurostat, authors' own calculations.

European Commission included Elia Group and Engie Belgium among the industry representatives participating in its November 2025 high-level roundtable on digitalisation and AI in the energy sector, where discussions addressed the potential of AI to make European energy grids more flexible, resilient and efficient (European Commission, 2025). Despite these country-specific characteristics, other sectors are overall comparable across countries.

### Focus: AI in Spain's pharmaceutical industry

A more granular analysis on a sample of 33 European countries (EU27 plus Albania, Bosnia and Herzegovina, Montenegro, Serbia, Turkey and Norway) and 32 sectors (Annex 7.3) yielded an interesting result: the **pharmaceutical industry** (NACE C21 in Eurostat) has emerged as a notable adopter of AI tools, a trend in which **Spanish companies** have achieved exceptional results.

Spain has the world's ninth-largest pharmaceutical market, generating an estimated €27.2 billion in value added in 2023 (1.9% of GDP) and more than 242,000 jobs

([Afi, 2025](#)). This is coupled with a strong **research** base: in 2024, pharmaceutical companies invested €1.647 billion in R&D, up 14.5% from 2023. Moreover, the extensive network of 700 R&D centres, public and private hospitals, universities and research institutes all contribute to strengthening the collaboration between companies and the health system.

At national level, the [AI Strategy 2024](#) mobilised €1.5 billion for 2024–2025 to strengthen computing infrastructure, data access, Spanish-language models, business and public-sector adoption, and responsible governance. One of the associated initiatives, [Spain Neurotech](#), develops advanced neurotechnological tools and promotes the ethical use of brain-computer interfaces. In parallel, the [2021 Digital Health Strategy of the National Health System](#) promotes interoperability, the digital transformation of healthcare services and the secondary use of health data for research, innovation and public policy. Training and skilling initiatives at the regional level (see Section 4.6) are also central conditions for converting digital investment into productivity gains.

AI in the Spanish pharmaceutical sector is being deployed across the **full medicines value chain**. Reported applications of AI technologies include molecule and target discovery, clinical-trial design and monitoring, advanced analytics, automated document workflows, computer vision and quality control in manufacturing, predictive maintenance, supply-chain optimisation, pharmacovigilance and digital health ([Farmaindustria, 2026](#)), showing a commitment to integrate AI at all stages of the production process.

Taken together, these characteristics help explain why Spain performs strongly in AI adoption in a non-ICT sector: broad implementation, scale and industrial specialisation are combined with research capability, clinical data, collaborative institutions and a highly qualified workforce. They also suggest that the main policy challenge is not merely to finance AI tools, but to strengthen data quality and interoperability, regulatory certainty, cybersecurity, access for SMEs and workforce capabilities.

The descriptive evidence establishes three patterns that frame the regression analysis: AI adoption is heterogeneous across European countries, monotonically increasing in firm size, and concentrated in knowledge-intensive sectors. The fixed-effect structure introduced in the next section is designed to net out these dimensions, so that the estimated relationship between AI adoption and economic outcomes reflects within-cell variation rather than compositional differences.

### 3.3 Empirical analysis

The empirical analysis proceeds in two stages. We first estimate the effect of AI adoption on labour productivity. Then we further examine the relationship between (i) different AI technologies and (ii) AI purposes and labour productivity.

## Labour Productivity Fixed-Effect Regression

We first investigate the relation between AI adoption and labour productivity in Europe. The dependent variable in the baseline specification is the natural logarithm of labour productivity, defined as the ratio of aggregate operating revenue to aggregate employment within each country × sector × size × age-group cell<sup>6</sup>. The empirical specification is:

$$\ln(LP)_{c,s,z,a,t} = \beta \cdot AI_{c,s,t} + \gamma X_{c,s,z,a,t-1} + \mu_{ct} + \delta_s + \theta_z + \phi_a + \varepsilon_{c,s,z,a,t} \quad (1)$$

where  $\mu_{ct}$  is a country × year fixed effect controlling for country-specific shocks over time,  $\delta_s$  is a sector fixed effect,  $\theta_z$  is a size-class fixed effect, and  $\phi_a$  is an age-group fixed effect. The control variables  $X$  include lagged investment, lagged leverage, and lagged logarithm of total assets, all measured at the cell level.

The choice of controls and lag structure was inspired by the EIB Working Paper 2026/02. We run the model with four specifications: contemporaneous AI without controls (A); contemporaneous AI with controls (B); one-year lagged AI without controls (C); and one-year lagged AI with controls (D).<sup>7</sup> Standard errors are clustered at the country × sector level.

Table 1 reports the results of estimating equation (A) with log labour productivity as the dependent variable, including country × year, sector, size-class, and age-group fixed effects. The contemporaneous AI adoption rate is positively and significantly associated with labour productivity across both the baseline and controlled specifications. In model (A), a **one-percentage-point increase in the sectoral AI adoption rate is associated with a 0.33 percent<sup>8</sup>** increase in labour productivity ( $p < 0.05$ ). In model (B), conditional on lagged investment, leverage, and firm scale, the coefficient falls modestly to 0.286 but remains significant at the five percent level, suggesting that the raw correlation is not driven by systematic differences in capital intensity or financial structure across high- and low-adoption cells.

The one-period lagged specifications show a broadly consistent but somewhat weaker pattern. The estimated coefficient for lagged AI adoption (model C) is 0.308 and is marginally significant in the baseline ( $p < 0.10$ ), whereas the addition of controls (D) reduces it to 0.214, and below significance thresholds. Taken together, the contemporaneous and lagged results are directionally consistent and do not provide evidence of negative or null associations with productivity.

Among the controls, lagged logarithm of total assets enters with a coefficient of approximately 0.140-0.143 across both controlled specifications ( $p < 0.001$ ), consistent with scale economies in production. Lagged leverage is also positively associated with productivity, with coefficients ranging from 0.228 to 0.295 ( $p < 0.05$  or smaller), which likely

<sup>6</sup> We chose this measure of labour productivity over other commonly used ones, such as *value added per employee*, due to lack of reliable data for these alternative indicators in the Orbis database.

<sup>7</sup> The contemporaneous models include AI adoption data for 2021, 2023 and 2024, while 2022 and 2025 are excluded due to insufficient and/or unreliable data. The lagged models use a shorter estimation sample, with 2021 and 2023 AI adoption data used to estimate the lagged relationships in 2022 and 2024, respectively.

<sup>8</sup> Corresponding to a coefficient of 0.331 log points when AI adoption is measured on a 0 to 1 scale. A one-percentage-point increase in AI adoption is therefore associated with an estimated 0.33% increase in labour productivity, calculated as  $e^{(0.331 \times 0.01)} - 1 = 0.33\%$ . For small changes, the log-point and percentage interpretations are approximately equivalent.

reflects survivorship: leveraged cells that remain in the sample tend to be those with sufficient cash flow to service debt. Lagged investment is small in magnitude, indicating that within-cell variation in capital expenditure explains little additional productivity variation once scale and employer-based firm size are controlled for.

**Table 1. Fixed effect regression results on labour productivity and AI adoption.**

|                                 | <i>AI (t)</i>      | <i>AI (t) +<br/>Controls</i> | <i>AI (t-1)</i>   | <i>AI (t-1) +<br/>Controls</i> |
|---------------------------------|--------------------|------------------------------|-------------------|--------------------------------|
|                                 | (A)                | (B)                          | (C)               | (D)                            |
| <i>ai_adoption</i>              | 0.331**<br>(0.139) | 0.286**<br>(0.120)           |                   |                                |
| <i>total_investment_lag</i>     |                    | 0.000***<br>(0.000)          |                   | 0.000***<br>(0.000)            |
| <i>leverage_lag</i>             |                    | 0.295**<br>(0.114)           |                   | 0.228*<br>(0.117)              |
| <i>ln_assets_lag</i>            |                    | 0.140***<br>(0.009)          |                   | 0.143***<br>(0.009)            |
| <i>ai_adoption_lag</i>          |                    |                              | 0.308*<br>(0.179) | 0.214<br>(0.159)               |
| <i>Num. Obs.</i>                | 11,787             | 11,692                       | 7,742             | 7,742                          |
| <i>R<sup>2</sup></i>            | 0.587              | 0.632                        | 0.588             | 0.631                          |
| <i>R<sup>2</sup>Adj.</i>        | 0.583              | 0.628                        | 0.584             | 0.626                          |
| <i>R<sup>2</sup>Within</i>      | 0.001              | 0.103                        | 0.001             | 0.104                          |
| <i>R<sup>2</sup>Within Adj.</i> | 0.001              | 0.103                        | 0.001             | 0.103                          |
| <i>AIC</i>                      | 24090.1            | 22413.0                      | 15690.3           | 14856.1                        |
| <i>BIC</i>                      | 24952.9            | 23297.0                      | 16330.1           | 15516.8                        |
| <i>RMSE</i>                     | 0.67               | 0.62                         | 0.66              | 0.62                           |
| <i>FE: country x year</i>       | X                  | X                            | X                 | X                              |
| <i>FE: nace_group</i>           | X                  | X                            | X                 | X                              |
| <i>FE: size_category</i>        | X                  | X                            | X                 | X                              |
| <i>FE: age_group</i>            | X                  | X                            | X                 | X                              |

Data: Eurostat and Orbis, authors' own calculation. P-values shown as \* < 0.1, \*\* < 0.05, \*\*\* < 0.01.

$R^2$  is below 0.001 in specifications (A) and (C), confirming that AI adoption alone explains a minimal share of the within-cell time-series variation in productivity. The controlled specifications raise the within- $R^2$  to approximately 0.103-0.104. This pattern is consistent with the literature in which technology adoption effects operate primarily in the cross-sectional dimension, rather than through the year-on-year dynamics that within-estimators identify. The overall  $R^2$  of 0.587-0.632 reflects the substantial explanatory power of the fixed-effect structure.

### Extensions: AI technologies and AI purposes

Different AI technologies automate different production tasks and may therefore affect productivity through different channels and in varying degrees. In Eurostat ICT usage in enterprises survey (2026), a distinction is made between *AI technologies* and *AI purposes*. The former refers to different technical methods that firms might employ (e.g., image recognition; process automation; autonomous robotics etc.). AI purposes instead refer to the business applications of AI, that is, the functions for which it is used. These include, for

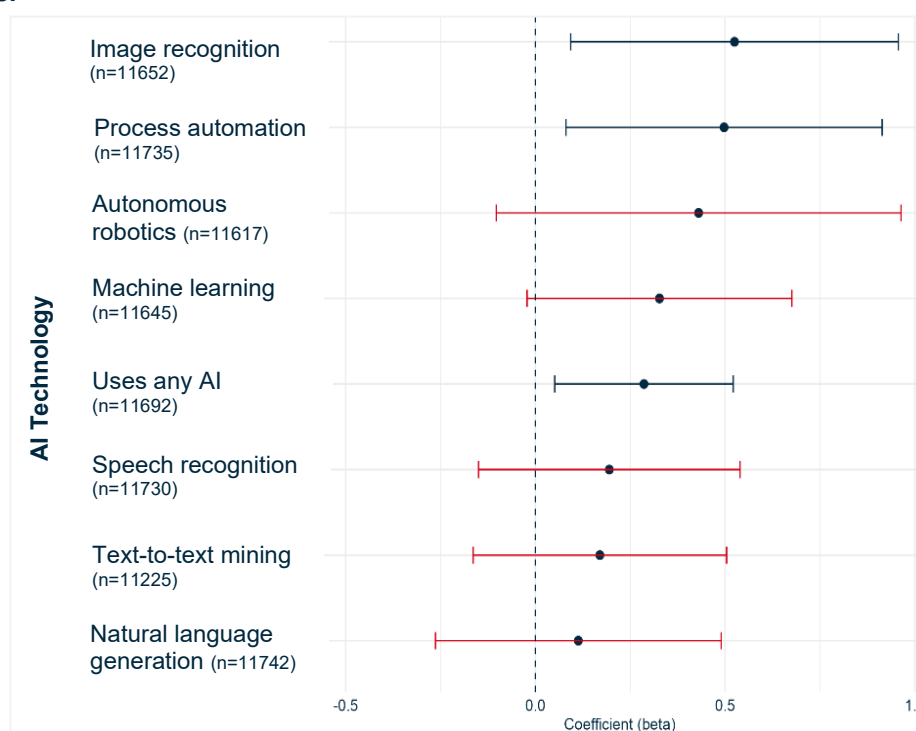
example, marketing and sales, logistics, R&D and accounting. Some AI technologies might be more linked to increases in labour productivity than others. Similarly, AI adoption might be associated with higher productivity levels when it is deployed in specific use cases.

To identify which *dimensions* of AI adoption are most closely associated with labour productivity, we re-estimate the controlled baseline fixed-effects specification (model B) for different (i) AI technologies and (ii) AI purposes sub-indicators reported in the Eurostat ICT usage in enterprises survey (2026), while holding the same control variables and fixed-effects structure.

## AI technologies and labour productivity

We first perform the analysis on different AI technologies. The resulting coefficient vectors are displayed as a forest plot with 95 percent confidence intervals (Figure 5). The sample sizes vary across sub-indicators, but remain large overall, ranging from approximately 3,600 to 11,800 cell-year observations.

**Figure 5. Estimated coefficients from fixed-effects regressions of labour productivity on different AI technologies.**



Note: Horizontal lines denote 95% confidence intervals. Colour codes shown as blue: p-value < 0.05, red: p-value > 0.05. Data: Eurostat and Orbis, authors' own calculations.

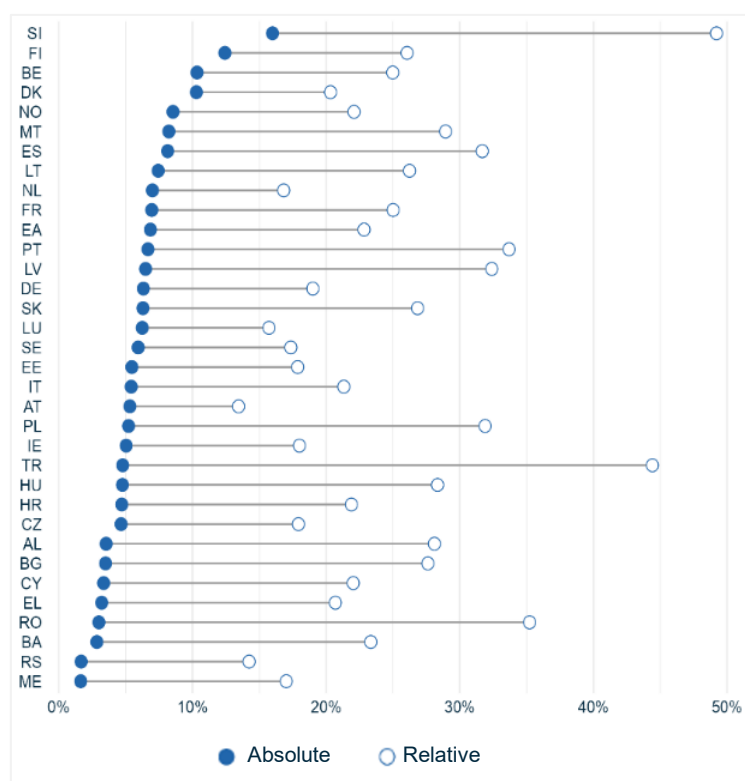
Among the eight technology-specific indicators, two emerge with statistically significant positive associations. **AI-based image recognition** (TIR, n = 11,852) returns the largest point estimate in the technology panel, with a coefficient above 0.5. **AI-based process automation** (TPA, n = 11,735) similarly shows a positive and statistically significant association, with a point estimate in the region of 0.5. This suggests that firms operating in sectors with higher adoption of automated workflow tools are meaningfully more productive after controls. The remaining technology indicators are estimated imprecisely, all yielding point estimates that are positive or close to zero, but whose confidence intervals span zero.

AI-based image recognition (TIR) refers to technologies able to identify or classify objects and persons from images or video (Eurostat, 2026). It is applied in the manufacturing sector for activities like automated quality inspection, defect detection, and production monitoring, although it is also extensively used in healthcare for analysing medical images such as X-rays, CT scans, and retinal scans. By automating visual inspection tasks, accuracy is improved and labour intensity reduced, leading to considerable efficiency and productivity gains.

AI-based process automation (TPA), instead, supports the automation of routine business workflows and decision-making processes (Eurostat, 2026). In service industries such as finance, business services, retail, and logistics, it is used for tasks like invoice processing, procurement, customer service, supply-chain management, and scheduling. It also has applications in manufacturing, notably in production planning and inventory management. Its positive relationship with labour productivity reflects its ability to streamline processes, reduce coordination costs, and enable employees to focus on higher value-added activities. Overall, the significance of AI-based image recognition and process automation is reasonable since both technologies directly reduce the labour required for routine tasks and are widely used in a variety of sectors.

While the regression results provide valuable insights into the AI technologies most strongly associated with higher labour productivity, they do not indicate how widespread these applications are across Europe. To provide additional context, we further the analysis by examining the adoption rates of these AI technologies in different European countries.

**Figure 6. Adoption of AI-based image recognition (TIR) by countries, 2025**



Data: Eurostat, authors' own calculation

Figures 6 and 7 thus depict the distribution of adoption rates for AI-based image recognition

(Figure 6) and AI-based process automation (Figure 7) across several European countries. The graphs include both absolute adoption rates of the considered technology, and the adoption relative to overall AI adoption (TANY). While the former captures technology diffusion, the latter provides insights into the technological mix across firms in a specific country. We use 2025 data for the non-financial economy (sectors C10–S951, excluding K in Eurostat).

TIR adoption in Europe appears heterogeneous (Figure 6), though all countries report relatively low rates of absolute adoption (less than 20%). Slovenia stands out as the country with the highest absolute (16%) and relative (49%) adoption rates, meaning that Slovenian firms are among Europe's most intensive users of TIR and that nearly half of the firms already using AI employ this technology. Romania, despite having the lowest AI adoption rate in Europe (TANY: 5.2% in Fig.1 and 2), exhibits one of the highest relative TIR adoption rates, with 35% of its AI-adopting companies using TIR technologies, thus indicating a high degree of specialization. Countries like Germany, France, Sweden and the Netherlands show higher absolute adoption, but much lower relative ratios, pointing to a more diverse use of AI technologies rather than a specific focus on image recognition.

**Figure 7. Adoption of AI-based process automation (TPA) by countries, 2025**

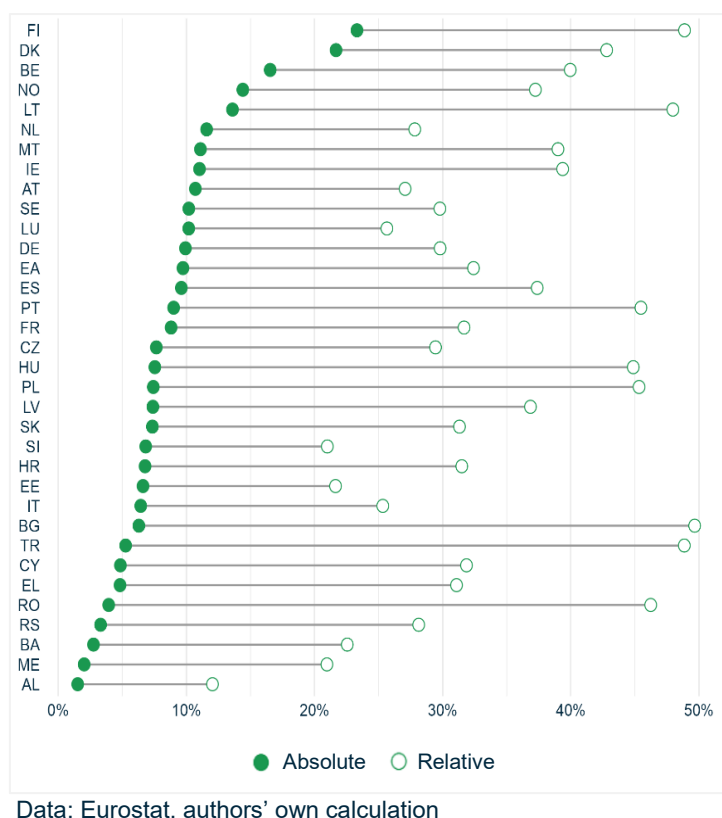


Figure 7 shows that AI-based process automation (TPA) is overall a more widely diffused AI technology compared to image recognition, with many countries clustering along the 7-15% range. Relative ratios, however, reveal significant variation across economies.

Lithuania, for examples, displays both a relatively high absolute adoption and one of the highest TPA-to-TANY ratios, indicating both broad diffusion and strong specialization in process automation. By contrast, Bulgaria, Turkey and Romania display low absolute TPA

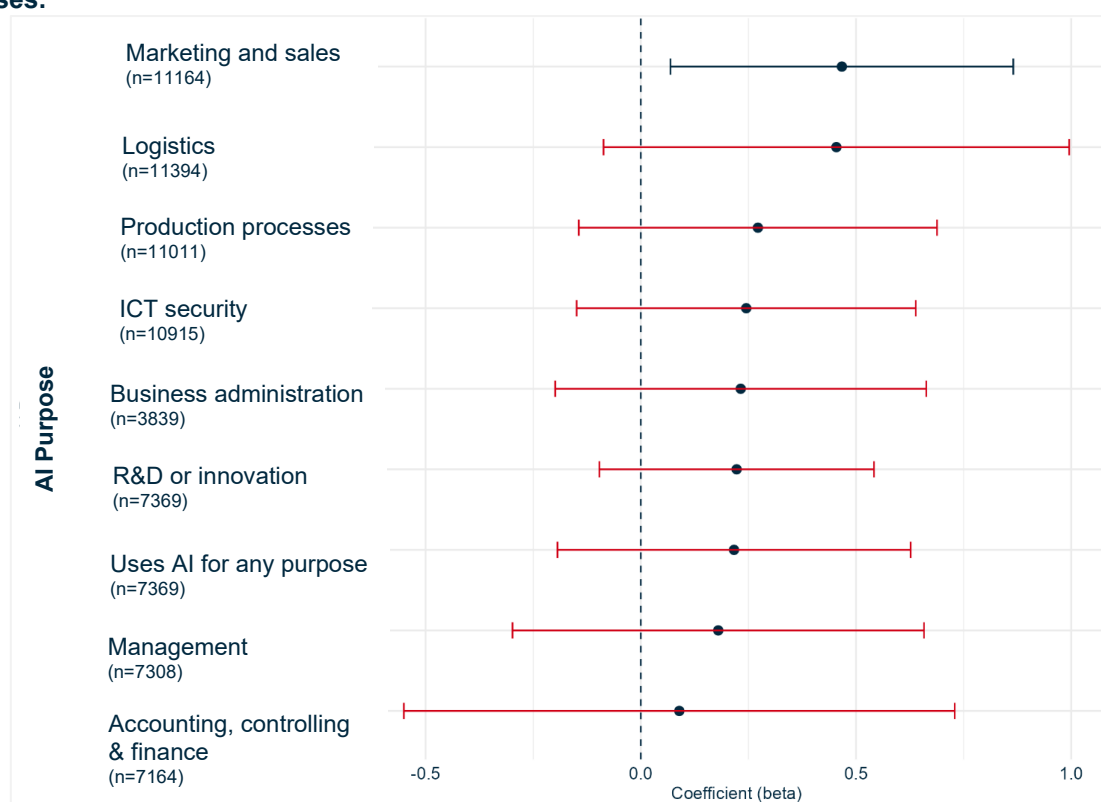
adoption but very high relative ratios, implying that firms adopting AI tend to concentrate on process automation rather than employing a wider variety of AI technologies.

## AI purposes and labour productivity

In this section, we differentiate between different types of AI purposes and look at their relationship with labour productivity. Among the various AI purposes, **marketing and sales** (PMS,  $n=11,164$ ) is associated with the largest and most precisely estimated coefficient, just under 0.5, with a confidence interval that excludes zero (Figure 8). The other investigated AI purposes all had coefficients whose confidence interval included zero and thus cannot be reliably interpreted.

The significance of marketing and sales suggests that productivity gains are concentrated in sectors where AI is used to support customer acquisition, targeting, and revenue generation. This is notably in line with the literature on the productivity gains of AI in customer service (Brynjolfsson et al., 2023).

**Figure 8. Estimated coefficients from fixed-effects regressions of labour productivity on different AI purposes.**



Data: Eurostat and Orbis, authors' own calculations. Colour codes shown as blue:  $p\text{-value} < 0.05$ , red:  $p\text{-value} > 0.05$ .

Figure 9 plots the distribution of marketing and sales (PMS) across European countries, both in their absolute and relative-to-TANY values. Data refers to 2025 and considers the non-financial sectors of the economy (in Eurostat, sectors C10–S951, excluding K). The absolute values capture the share of companies in that country using AI technologies for marketing and sales purposes, whereas the relative rate reflects the use of AI for PMS relative to other use cases.

**Figure 9. AI adoption for marketing and sales by countries, 2025**



Data: Eurostat, authors' own calculation.

Similarly to the previous sub-indicators, substantial heterogeneity can also be observed in this dimension. Most countries show absolute rates below 15%, with Finland standing out as the clear leader. Relative adoption, however, is higher and less dispersed than for AI technologies, centring closer to the 0.25-0.50 range. Overall, this points to marketing and sales being one of the primary applications of AI among European firms already using AI. Several countries – such as Sweden, Czechia, Latvia, Poland and Cyprus – show relative ratios above 50%, indicating that more than half of AI-adopting firms use AI for marketing and sales purposes. In contrast, countries such as Luxembourg and Slovakia display lower relative ratios, implying that AI is instead more frequently used for other business functions.

Overall, the analysis suggests that marketing and sales constitutes one of the most common uses of AI adoption across European firms. This pattern is consistent with the broader literature, which identifies customer-facing applications including customer segmentation, targeted advertising, recommendation systems, demand forecasting and customer relationship management - as among the earliest and most commercially accessible uses of AI. These applications typically require lower organisational restructuring than production-related AI and often generate rapid and measurable returns, making them particularly attractive during the initial stages of AI adoption.

Taken together, these findings indicate that the productivity benefits associated with AI adoption are not uniform across technologies or purposes in business activities. This heterogeneity suggests that the economic impact of AI depends not only on whether firms adopt AI, but also on the specific technologies implemented and on the organisational functions in which they are deployed.

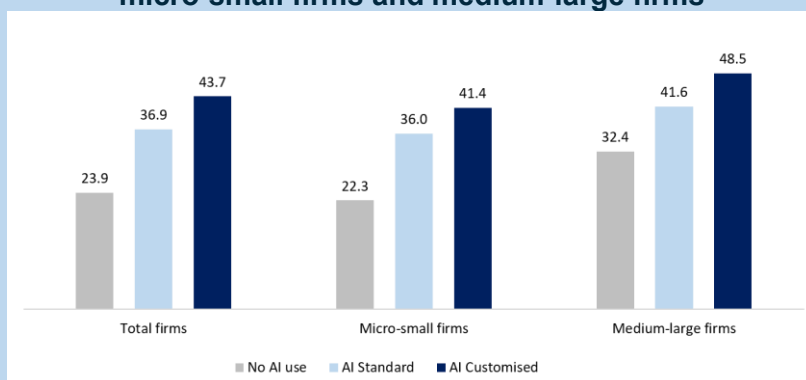
## Beyond AI Adoption: How Integration Shapes Firm Performance. Evidence from Italian Firms

Survey evidence by Istituto Guglielmo Tagliacarne – the Research Centre of the Italian Union of Chambers of Commerce (Unioncamere)<sup>1</sup> – on 4,500 Italian firms shows that it is not AI adoption alone, but rather its integration into business processes, that brings real advantages for companies.

AI adoption is not a purely technical process. Its strategic potential emerges when firms redesign workflows, reallocate tasks, retrain workers and adapt organisational structures. Standardised AI tools can reduce entry costs and allow for early AI experimentation. However, the capacity to generate more lasting economic value increasingly depends on whether the technology is adapted to firm-specific data, processes and strategic objectives.

Evidence gathered by the Research Centre Istituto Guglielmo Tagliacarne supports this interpretation. When distinguishing between firms using *customised AI solutions* versus *standard AI solutions*, the former are more likely to expect turnover growth compared to those relying exclusively on standardised applications: 43.7% compared with 36.9% (Figure 1).

**Figure 1. Share of firms expecting turnover growth, by type of AI tool used: total sample, micro-small firms and medium-large firms**



Source: Istituto Guglielmo Tagliacarne-Unioncamere survey

This result is supported by the econometric analysis: after controlling for a range of structural characteristics, including firm size, sector and geographical location, firms using customised or combined AI solutions are **5.1 percentage points more likely to expect an increase in turnover** than firms relying solely on standardised tools. The estimated effect is statistically significant (see Table 1, Model A in Annex 7.4).

This relationship is even stronger among small firms. For businesses with 5-49 employees, the probability of expecting turnover growth increases by 6.0 percentage points, and the effect remains statistically significant. Among medium-sized and large firms, the estimated effect is also positive, but not statistically significant.

Overall, from a policy perspective, these results show that AI availability alone is not enough. Firms, especially smaller ones, also need investment, organisational support and skills to adapt AI to their specific needs and turn it into a driver of competitiveness.

For a more extensive discussion on the benefits and risks of AI adoption on Italian firms, please see Figures 5, 6, 7 in Annex 7.4.

### 3.4 Limitations of the empirical research

There are several limitations in the interpretation of our results. First and most, since AI adoption microdata was not available throughout the research period for a large pool of European firms, we could not observe the effects of AI at the micro level: the main data source of the working paper, the Eurostat ICT usage in enterprises survey, uses aggregates, so we had to assign the adoption rates to Orbis observations as country-sector cell values rather than as direct measures. This means that the analysis identifies the association between sectoral AI diffusion and its outcomes, not the firm-level returns to adoption. These two should not be interpreted as equivalent.

The research design is also associational rather than causal. While the fixed-effect structure - a research design chosen because of the low number of years to observe - absorbs the differences across countries, sectors, size, and age groups, and the lagged specifications guard against the most immediate forms of reverse causation, we cannot rule out time-varying confounders that jointly drive AI adoption and productivity within cells, such as unobserved shocks or investments in skills and intangibles. The estimates should therefore be read as conditional correlations with a productivity channel, not as direct effects.

Lastly, the sample is subject to some availability and selection bias. Orbis over-represents larger and incorporated firms and is unevenly populated across countries. Also, Eurostat observations flagged as unreliable were dropped, as well as the whole financial sector (K in Eurostat). The resulting cells may not be fully representative of the underlying European business population. Finally, survivorship bias may influence the estimated coefficients of some controls, as the firms observed throughout the panel may not be representative of the broader business population. For instance, the positive relationship between leverage and productivity may partly reflect the survival of financially stronger firms.

Despite these limitations, the findings remain relevant for innovation and SME policy and for the work of European chambers of commerce. The clear divide in AI adoption between different European countries and regions points to both obstacles and opportunities. It helps identify where the gaps are most acute, and the kind of companies (SMEs), sectors, and geographical regions where AI adoption is weaker.

Moreover, as the productivity gains associated with the current phase of AI diffusion are concentrated in applications closely aligned with day-to-day business operations, such as image recognition, process automation, and marketing and sales, there is scope for targeted, near-term policy interventions. These measures fall largely within the remit of business support organisations and could facilitate the broader adoption and effective utilisation of AI technologies among firms.

## 4. Best practices from European chambers of commerce

The findings highlight AI's transformative potential for businesses and the economy. Businesses should thus be encouraged to explore how they can use this technology both to gain a competitive advantage and to avoid falling behind. However, AI adoption presents challenges that go beyond those associated with digitalisation. The main barriers to digitalisation are well known: limited skills, insufficient financing and resources, and gaps in digital skills. For AI adoption, these challenges are compounded by regulatory uncertainty,

trust, data availability, governance and, most importantly, by the practical question of how to integrate AI sensibly into existing workflows.

Chambers of commerce and industry are very familiar with the challenges posed by digitalisation and have long offered their businesses-tailored support. They are therefore uniquely positioned to offer support in adopting AI, in addition to existing support on digitalisation. Recently, several chambers have expanded their offers to support businesses with AI use. The following section provides an overview of the measures different European chambers have taken to support their businesses with AI adoption. It serves as a showcase for best practices aimed at informing both policymakers as well as stakeholders of the chamber network.

## 4.1 Germany

The German Chamber of Commerce and Industry (DIHK) supports companies in adopting AI through a combination of legal guidance, practical orientation and concrete business examples. Its campaign [“KI im Klartext: Vom Paragraphen zur Praxis”](#) (*AI in Plain Language: From Regulation to Practice*) addresses the main regulatory questions companies need to consider when introducing AI, including the EU AI Act, data protection, licensing, contract law and liability issues. The goal is to help businesses understand not only the opportunities of AI, but also the legal and organisational requirements that come with its use. The campaign is complemented by podcast episodes featuring legal expertise, which discuss how companies can implement AI in line with applicable rules and integrate it responsibly into their organisation.

In addition, the DIHK points companies towards practical learning formats, including the [“BreAlkfast” webinar series](#), where companies can learn how AI is already being used in everyday business operations. The central element of these webinars is the presentation of concrete use cases that make AI tangible and accessible for companies. The examples cover a broad range of operational fields, including media production, logistics, industry and production, sales and customer service, customer inquiry management, generative AI for business development, tourism and energy management. They illustrate practical applications such as improving transparency and loading efficiency in logistics with AI, supporting production processes, automating customer inquiries, analysing documents and offers, identifying new material combinations, or reducing energy consumption in hotel operations. By bringing together researchers, IT service providers and company practitioners, the DIHK’s use-case collection gives SMEs accessible entry points for identifying where AI could add value in their own workflows.

Aside from offering direct support to businesses, German regional chambers of commerce and industry (IHKs) are working towards addressing the skills gap, a central issue in digitalisation and AI. For instance, three regional chambers in Baden-Württemberg (IHK Stuttgart, IHK Karlsruhe, IHK Reutlingen) led the development of an upskilling programme dedicated to AI- and machine learning-related skills.

The pilot project started in 2020 and was managed in cooperation with the academic sector. The initial phase involved identifying specific companies’ needs by gathering direct businesses’ feedback. Structured interviews with employers, trainers and Vocational Education and Training (VET) schools were conducted to find out the exact kinds of skills and professional profiles companies needed. This resulted in an extensive reskilling and

upskilling program covering levels 4-6 of the European Qualifications Framework (EQF 4-6). The programme included a **Certificate in AI & Machine Learning** (EQF 4, approximately 100 hours); a **Certified AI Practitioner** course (EQF 5, approximately 440 hours) focused on identifying AI use cases and bridging business and IT functions; and a **Professional Bachelor in AI & Machine Learning** (EQF 6, approximately 1,250 hours) designed to prepare personnel to design and implement AI projects. The programme proved highly successful and is currently offered by 11 regional chambers, with further rollout planned across Germany.

Another initiative leading to more AI usage and AI literacy in relation to vocational education is the “KI-Scout” program. Apprentices can apply for the certificate course (“Zertifikatslehrgang”) in order to learn more about AI usage in their company, which takes around 50 hours divided between six training modules. The core of the program is the practical relevance. As part of their final projects, the apprentices identify possible use cases in their own companies, optimize AI usage or introduce new AI-based procedures. Therefore, both the companies and the apprentices benefit from the program.

## 4.2 Austria

In Austria, the Austrian Federal Economic Chamber (WKO) has centred its AI support around helping SMEs move from general awareness to company-specific rules and implementation. [The WKO's AI portal](#) brings together practical guidance, webinars and sector-oriented material under a single-entry point, encouraging businesses to explore the potential of AI applications for their own operations and to be prepared to use a technology expected to shape business practice in the coming years.

A distinctive element of the Austrian approach is the emphasis on internal company guidelines. The WKO's AI Guidelines for SMEs are designed to explain the use of AI in accessible language and help companies define how employees should use AI tools responsibly in daily work. This goes beyond general information provision: WKO also offers model guidelines and an online tool [that allows companies to adapt guidelines to their own needs](#), including the possibility to create individual AI rules for the workplace. This makes the Austrian case particularly relevant for SMEs that may not have the legal or HR capacity to develop such rules from scratch.

The WKO complements this guidance with practical learning formats. Its “KI in der Praxis” (*AI in practice*) webinar series, like DIHK's “BreAIkfast”, is available on demand and addresses practical, user-oriented subjects such as AI-based image generation, workflow automation and document processing. The annual **eDAY** event further positions AI as a prominent topic in Austria's digitalisation debate. Themes such as “Data, AI and Human Touch” connect SMEs with current technological trends and address concrete technology applications.

The Austrian case is also closely linked to the country's broader SME digitalisation support ecosystem. Through initiatives such as **KMU.DIGITAL** (which includes public financial support), the WKO connects AI-related guidance with advisory and implementation support for the digital transformation. This gives the Austrian model a specific focus: in addition to presenting AI use cases, it helps SMEs establish the organisational conditions for responsible AI use, translate general guidance into company-level rules and connect AI adoption with existing digitalisation and innovation support.

### 4.3. Luxembourg

Luxembourg has positioned artificial intelligence as a central element of its [Accelerating Digital Sovereignty 2030 strategy](#). Within this framework, the Luxembourg Chamber of Commerce plays an important role in supporting businesses throughout the AI adoption process. Similar to the initiatives described in Germany and Austria, the Chamber combines practical guidance, skills development and business support measures aimed particularly at SMEs. At the same time, it is closely integrated into a broader national ecosystem involving government bodies, innovation agencies, research institutions and training providers.

The Chamber's principal entry point for businesses is its **House of Entrepreneurship**, which implements the recently launched [SME support package for AI](#) together with the Ministry of the Economy and the Chamber of Skilled Trades for craft enterprises.

The programme is designed to help SMEs integrate artificial intelligence into day-to-day business operations. Eligible companies can receive public support covering up to 70% of eligible project costs for AI-related investments between €3,000 and €25,000 excluding VAT. The scheme is designed as more than a simple funding instrument. Companies receive support throughout the entire project lifecycle, beginning with an assessment of their AI readiness and business needs, followed by assistance in identifying relevant use cases, referral to a list of service providers registered in the programme, preparing funding applications and evaluating results after implementation.

This approach reflects a recurring theme among many chamber-led initiatives across Europe: helping firms move from a general interest in AI towards concrete business applications capable of generating measurable value.

A second pillar of the Luxembourg approach focuses on skills development. The **House of Training**, established by the Luxembourg Chamber of Commerce together with the Luxembourg Bankers' Association (ABBL), provides [continuing professional education in digital technologies and artificial intelligence](#). Following its principle that "professionals train professionals", the institution offers practical courses tailored to the needs of businesses and employees operating in the Luxembourg economy.

Recent initiatives include executive programmes dedicated to AI in the financial sector, helping managers and decision-makers better understand the opportunities, risks and regulatory implications associated with artificial intelligence.

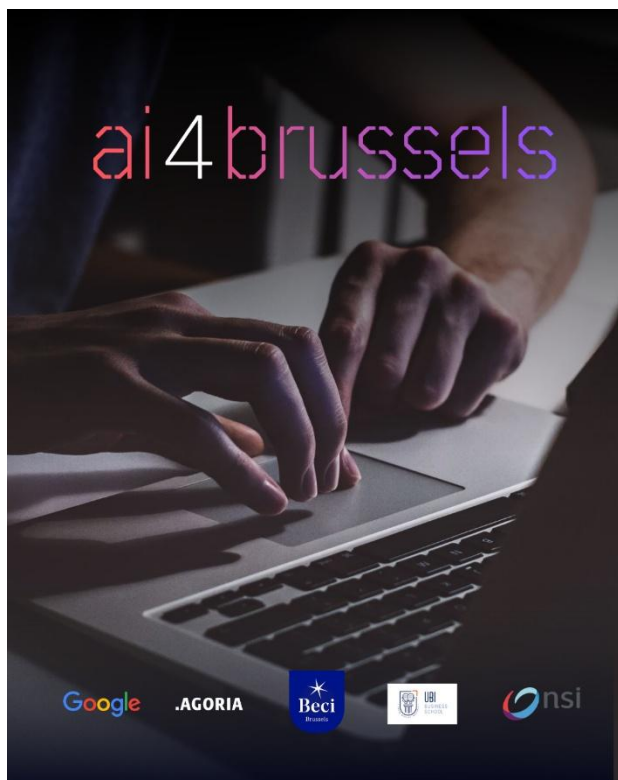
### 4.4 AI for Brussels: evidence from a regional chamber

While the previous sections centred around national chamber initiatives, the example of the **Brussels Chamber of Commerce and Industry (Beci)** provides a more granular perspective on how AI support can be delivered at regional level. Through its **AI4Brussels** initiative (2026–2029), Beci aims to train **10,000 companies**, primarily SMEs, in the practical use of artificial intelligence and support them in adapting their business models and workflows to AI-enabled tools.

The programme focuses on helping businesses identify practical applications that can generate immediate productivity gains in day-to-day operations, including email management, research, content creation and the automation of repetitive tasks. Participants are also introduced to widely used AI tools such as Microsoft Copilot, Claude and other productivity-oriented solutions.

A distinctive feature of the initiative is its strong local dimension. To maximise accessibility, training activities are rolled out across all **19 municipalities of the Brussels-Capital Region**, bringing support directly to businesses. Following an initial testing and refinement phase in 2026, the programme will be deployed at scale between 2027 and 2029.

As with many chamber-led initiatives, implementation relies on a broad ecosystem of partners. Beci collaborates with **NSI** to develop the methodology and train instructors, while **Google**, **Agoria** and **UBI** contribute expertise, training content and online learning modules. Local municipalities further support outreach through their communication channels, complementing Beci's own business networks.



The AI4Brussels initiative demonstrates how regional chambers can translate broader AI strategies into practical, locally accessible support measures. By combining proximity, hands-on training and strong partnerships, the programme provides SMEs with a structured pathway from AI awareness to business adoption.

#### **4.5 Spain: How regional chambers provide support for the healthcare sector**

Several regional initiatives demonstrate how Spanish chambers support the adoption of AI in healthcare and life sciences. The Terrassa Chamber of Commerce participates in the Vallès Occidental AI Hospital Challenge (RHIA-VO), which brings together hospitals, research organisations and technology providers to identify practical challenges and test AI solutions in clinical environments. The initiative supports collaboration between healthcare providers and technology developers and facilitates the validation of new solutions in real-world settings.

The Girona Chamber of Commerce contributes through its Health and Wellbeing Hub, which connects companies, startups, healthcare institutions, universities and research centres. The hub supports collaboration projects, technology validation and internationalisation activities, while also organising events on emerging technologies in healthcare. In 2026, for example, the Chamber hosted a conference dedicated to AI applications in the healthcare sector.

Other chambers focus on awareness-raising and facilitating access to support measures. The Valencia Chamber of Commerce promoted the Spanish Government's RedIA and RedIA Salud funding programmes, while the Madrid Chamber of Commerce participated in discussions on digitalisation, cloud computing and AI in healthcare through industry events and forums.

These examples show how the network of Spanish chambers of commerce contributes to furthering AI adoption through training and information, and by promoting funding opportunities and fostering collaboration between businesses, healthcare organisations, research institutions and technology providers. This role is particularly relevant in the pharmaceutical and healthcare sectors, where innovation often depends on cooperation across multiple actors and access to specialised expertise.

## 4.6 Italy

Unioncamere supports the digital transformation of micro, small and medium-sized enterprises through the national network of *Punti Impresa Digitale* (PID – Digital Enterprise Points), established within the Italian Chambers of Commerce. In 2026, this support is being further strengthened through the launch of **AI-Labs**: territorial, practice-oriented laboratories designed to help businesses understand, test and adopt AI solutions tailored to their specific needs. Complementing the PID network's existing awareness-raising, training and digital maturity assessment activities, AI-Labs move beyond general information towards more hands-on, use case-oriented support. A complementary service, **OrienterAI**, provides Chamber staff with a tool to assess companies' needs and direct them towards appropriate AI applications and business solutions.

This approach builds on the experience of **I-NEST**, the European Digital Innovation Hub coordinated by CNIT, through which Unioncamere and Dintec developed a model for bringing advanced digital technologies closer to SMEs. I-NEST combines the expertise of research organisations and specialised partners in artificial intelligence, high-performance computing and cybersecurity with the nationwide outreach capacity of the Italian Chambers of Commerce and their PID network. Through this ecosystem, businesses and public administrations can access a range of services, including digital maturity assessments, training, *test-before-invest* opportunities, technology scouting, networking and support in identifying relevant funding opportunities.

Unioncamere and Dintec are now scaling up this approach through their participation in four newly selected EDIH consortia: one coordinated by CNIT, which further develops the I-NEST model with a stronger focus on commerce, tourism and the cultural and creative industries, and three manufacturing-oriented hubs — **MIA 2**, **MAIX** and **PRIDE-CETMA** — coordinated respectively by MADE, BI-REX and CETMA.

Together, AI-Labs, OrienterAI and the EDIH partnerships provide SMEs with a structured pathway from awareness to implementation. They help businesses identify relevant AI use cases, build the necessary skills, test suitable solutions and reduce the uncertainty and risks often associated with technology adoption.

The Italian approach illustrates how chambers can act as intermediaries between highly specialised technological ecosystems and local businesses. By combining trusted proximity to SMEs with access to advanced expertise, the chamber network helps ensure that AI

adoption is not limited to large firms or technology-intensive sectors, but can increasingly benefit businesses across different regions and industries.

## **4.7 Slovenia**

The Chamber of Commerce and Industry of Slovenia (GZS) has developed a multi-layered approach to supporting the uptake of artificial intelligence in business, combining awareness-raising, practical guidance, skills development and ecosystem building. A central element is the Slovenian National Artificial Intelligence Competence Centre (KCUI), led by GZS in partnership with universities, research institutes and other business-support organisations. KCUI serves as a national entry point for companies and other organisations seeking to understand, adopt and use AI safely, responsibly and effectively. It provides access to training, expert advice, knowledge resources, use cases and AI solution providers, while helping companies identify where to start, assess their readiness and move from an initial idea towards implementation, with particular attention to the needs of SMEs.

This builds on work that GZS, through its [ICT Association of Slovenia](#) (ZIT), has been developing for several years through the [AI4SI – AI for Slovenia initiative](#). AI4SI was established to accelerate the transfer of AI research and expertise into business practice and to connect companies, technology providers, researchers and public-sector stakeholders. Its activities include sharing good practices, workshops and events, guidance on regulatory requirements and practical support for companies introducing AI. One of its key outputs is the [Guide to the Deployment of Artificial Intelligence in Business](#), which provides managers and SMEs with a structured approach to AI adoption, covering organisational culture, skills, data, infrastructure, generative AI, risk management and the EU AI Act.

Alongside these broader initiatives, ZIT regularly provides its members with training and expert events on current AI topics. These activities address both technological developments and their business, organisational, legal and skills implications, enabling companies to learn from experts as well as from the practical experience of peers.

Since January 2026, GZS has through KCUI reached around 2,000 participants through training and awareness activities. Its 2026 survey found that around 65% of responding organisations are using or testing AI, while 44% have AI in production or are scaling it systematically, showing the need to help companies move from experimentation to wider implementation.

The Slovenian chamber approach therefore combines a long-term community-building initiative with a national competence centre and continuous member-oriented learning. Its main strength is the focus on shortening the path from awareness to practical adoption, particularly for SMEs: helping companies develop the necessary competences, connect with relevant expertise and partners, manage risks and translate AI opportunities into measurable improvements in productivity, competitiveness and innovation.

## **4.8 Hungary: AI awareness through a nationwide chamber training programme**

The **Hungarian Chamber of Commerce and Industry (MKIK)** launched the artificial

intelligence seminar series **Digital Wake-Up (Digitális Ébresztő)** in May 2025 as part of the professional forums of the **Modern Enterprises Programme 2.0 (MVP 2.0)**. The initiative was designed to introduce SMEs to the practical business applications of AI and to provide an accessible entry point for companies interested in the technology but lacking prior technical expertise.

The programme was implemented through the nationwide chamber network and reached a considerable scale within a short period. During the 2025 phase, **44 events** were organised across Hungary, demonstrating how a standardised and practice-oriented training format can be delivered with broad territorial coverage through cooperation between regional chambers.

Participation in the seminars was free of charge and subject to prior registration. The sessions primarily targeted SMEs seeking to understand the business relevance of AI and its potential applications in everyday operations. The programme was led by experts with extensive experience in IT, digital business development, and corporate and higher-education training, translating the functioning of generative AI into practical business use cases.

The seminars followed a structured **90-minute format** consisting of three consecutive modules.

First, participants explored the **business relevance of AI and common concerns surrounding its use**. Drawing on real business cases, companies identified repetitive, analytical, creative, or time-consuming tasks where AI could provide support. Discussions also addressed issues such as data handling, legal responsibility, inaccurate outputs, and concerns about job displacement, helping participants distinguish between business opportunities and areas requiring human oversight.

The second module focused on **operating principles, task assignment, and control mechanisms**. Participants were introduced to the fundamentals of language models, their capabilities, and their limitations. Through twelve prompting principles, they learned how to define roles, tasks, contextual information, expected outputs, and verification criteria. Particular attention was given to protecting sensitive information, verifying sources and factual accuracy, and ensuring final human approval of AI-generated content.

The final module centred on **hands-on experimentation and participant engagement**. Using their own devices, participants completed practical exercises including the creation of images, product photographs and promotional materials, website oncepts, spreadsheet analysis, and the drafting of marketing, social media, and administrative content. They also compared outputs from different AI tools.

## **5. Policy recommendations**

This paper's findings provide encouraging evidence on AI adoption and its association with higher labour productivity. At the same time, AI adoption remains highly uneven across countries, sectors and firm sizes, suggesting considerable scope for further diffusion across the European economy. As AI becomes an increasingly critical element of business competitiveness, policymakers will need to address not only the barriers that continue to limit adoption, but also the broader question of ensuring reliable and long-term access to

the technologies underpinning Europe's AI transformation. Finally, the chamber initiatives presented in this paper demonstrate the important role that local business ecosystems can play in supporting AI adoption, particularly among SMEs, by translating technological developments into practical use cases, training opportunities and implementation support. The following recommendations build on these findings.

### **Accelerate AI adoption among SMEs**

The sizeable gap in AI adoption between large firms and SMEs represents one of the most important barriers to a broad-based AI transformation in Europe. While larger businesses are generally better equipped to invest in technology, skills and organisational change, many SMEs face resource constraints that limit their capacity to experiment with and deploy AI solutions.

Policymakers should therefore strengthen support mechanisms that reduce the costs and risks associated with AI adoption. This includes expanding access to advisory services, demonstration projects, testing environments and peer-learning networks that help SMEs identify practical business applications of AI. The chamber initiatives presented in this paper demonstrate that businesses benefit substantially from concrete use cases and implementation support. With the Apply AI Strategy, the AI Continent Action plan and the establishment of AI Factories and European Digital Innovation Hubs (EDIHs), the EU has several strategies in place that aim to foster AI adoption. The Commission should regularly evaluate whether these initiatives contribute to the goal of fostering AI adoption especially for SMEs.

### **Invest in skills and organisational readiness**

The evidence reviewed in this paper suggests that the productivity benefits of AI depend heavily on complementary investments. Technology alone is unlikely to generate substantial gains unless businesses possess the skills, organisational structures and managerial capabilities required to integrate AI into existing workflows.

Addressing AI-related skills shortages should therefore be a priority at both European and national level. This includes strengthening AI-related education and vocational training, expanding opportunities for lifelong learning and supporting workforce upskilling within companies. Particular attention should be paid to SMEs, which often lack the capacity to provide extensive internal training. Chambers of commerce, vocational education providers and industry associations can play an important role in translating technical developments into practical business knowledge and sector-specific training opportunities. It is important that SMEs are not left alone in providing AI literacy training as required by Article 4 of the AI Act. Member States and the Commission should provide tangible support to help SMEs train their staff to use AI responsibly and productively.

### **Improve access to digital infrastructure, data and computing resources**

AI increasingly depends on access to high-quality data, computing power and digital infrastructure. While Europe has made important progress in strengthening its digital capabilities, access remains uneven, particularly for smaller firms and businesses operating outside major innovation hubs.

Continued investment in digital infrastructure, high-performance computing facilities and AI

testing environments should therefore remain a priority. At the same time, policymakers should work towards improving access to data and promoting secure and trustworthy data-sharing frameworks that allow businesses to develop and deploy AI solutions more effectively. Strengthening European digital capacities is not only important for innovation, but also for ensuring that European businesses remain competitive in an increasingly AI-driven global economy. The Tech Sovereignty Package is an important step in that direction. Accelerating the establishment of a European Data Center Infrastructure as well as a sovereign Chips production should be of priority given the geopolitical circumstances.

### **Address regional and sectoral adoption gaps**

The empirical analysis highlights a clear geographical divide in AI adoption across Europe. Businesses in Nordic and several Western European countries generally display significantly higher adoption rates than firms in parts of Southern and Eastern Europe. Similar disparities exist across sectors, with AI adoption concentrated in knowledge-intensive industries while remaining comparatively limited in sectors such as construction, trade and parts of manufacturing.

This suggests that a one-size-fits-all policy approach is unlikely to be sufficient. Future support measures should be targeted towards regions, sectors and firms where adoption remains particularly low. Greater attention should also be paid to sharing successful practices between countries and regions in order to accelerate diffusion across the Single Market and prevent existing competitiveness gaps from widening further. A potential barrier to AI adoption and its productive employment can also be different languages, especially in the case of LLMs. While languages like English, Spanish and French are spoken by hundreds of millions of people across the world, there are many European languages that are not spoken as commonly (e.g. Lithuanian, Latvian, Estonia or Hungarian just to name a few). Consequently, the training data used for LLMs is not available in the same quantity as in other language. This may limit AI adoption especially in office settings in countries which languages are not widely spoken. It remains a question for future research and for policy makers to tackle this challenge.

### **Ensure regulatory clarity and build trust**

A predictable and innovation-friendly regulatory environment will be essential for accelerating AI adoption. While trustworthy AI and effective safeguards remain important, businesses require clear guidance and legal certainty in order to invest confidently in AI solutions.

The implementation of the EU AI Act should therefore be accompanied by practical guidance, sector-specific examples and support measures that help businesses understand and comply with their obligations. Particular attention should be paid to the needs of SMEs, which often have limited legal and compliance resources. Regulatory clarity, combined with support for AI literacy and responsible deployment, will be critical to strengthening trust and encouraging wider uptake.

### **Conclusion**

The paper's findings overall suggest that AI could be an important driver of productivity for European businesses. On the whole, AI adoption in Europe is increasing, yet it remains

highly uneven across European countries, sectors and firm sizes, with SMEs clearly and consistently lagging behind. The positive association between AI adoption and labour productivity, specifically for (i) AI-based image recognition, (ii) AI-based process automation, and (iii) marketing and sales, indicates that AI can be a valuable tool for businesses, and lead to tangible gains. However, translating these opportunities into actual productivity increases hinges heavily on complementary factors such as investments in skills and organisational capabilities, infrastructure, data availability, a predictable regulatory environment, as well as on providing special support to the regions and companies currently falling behind. European chambers of commerce and industry offer valuable examples of the kind of support businesses need, not only to adopt, but to better understand the role that AI can play in streamlining their activities and overall making our economy more competitive.

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## 7. Annexes

### 7.1 Sectors covered

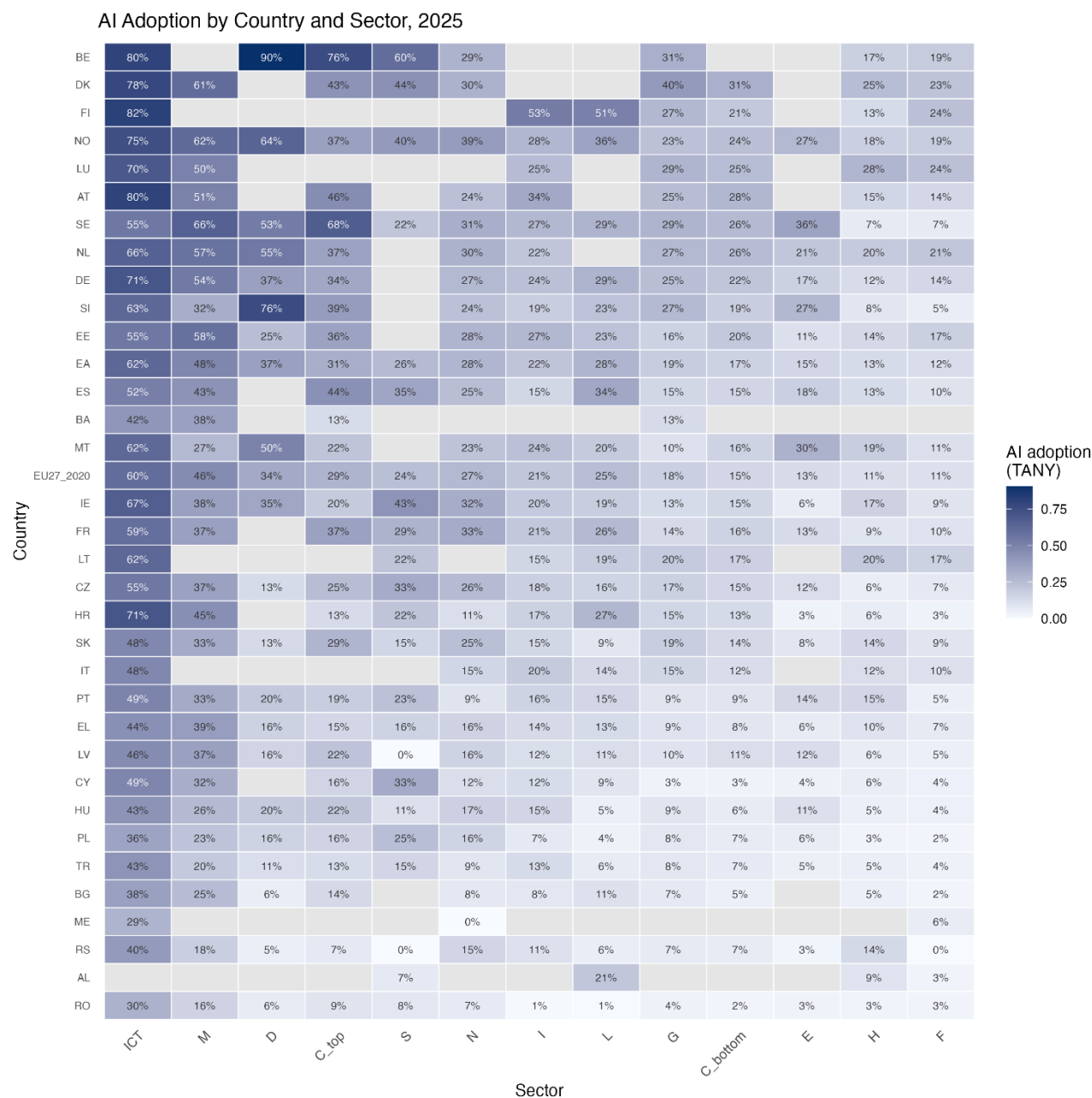
Our research examined the following 31 sectors:

| <b>Code</b>          | <b>Eurostat sector name</b>                                                                                                                                                 |
|----------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>C10-C12</b>       | Manufacture of food products, beverages and tobacco products                                                                                                                |
| <b>C13-C15</b>       | Manufacture of textiles, wearing apparel, leather and related products                                                                                                      |
| <b>C16-C18</b>       | Manufacture of wood, paper, printing and reproduction                                                                                                                       |
| <b>C19</b>           | Manufacture of coke and refined petroleum products                                                                                                                          |
| <b>C20</b>           | Manufacture of chemicals and chemical products                                                                                                                              |
| <b>C21</b>           | Manufacture of basic pharmaceutical products and pharmaceutical preparations                                                                                                |
| <b>C22-C23</b>       | Manufacture of rubber and plastic products and other non-metallic mineral products                                                                                          |
| <b>C24-C25</b>       | Manufacture of basic metals and fabricated metal products, except machinery and equipment                                                                                   |
| <b>C26</b>           | Manufacture of computer, electronic and optical products                                                                                                                    |
| <b>C27</b>           | Manufacture of electrical equipment                                                                                                                                         |
| <b>C28</b>           | Manufacture of machinery and equipment n.e.c.                                                                                                                               |
| <b>C29-C30</b>       | Manufacture of motor vehicles, trailers and semi-trailers; manufacture of other transport equipment                                                                         |
| <b>C31-C33</b>       | Manufacture of furniture; other manufacturing; repair and installation of machinery and equipment                                                                           |
| <b>D35</b>           | Electricity, gas, steam and air conditioning supply                                                                                                                         |
| <b>E</b>             | Water supply; sewerage, waste management and remediation activities                                                                                                         |
| <b>F</b>             | Construction                                                                                                                                                                |
| <b>G45</b>           | Wholesale and retail trade and repair of motor vehicles and motorcycles                                                                                                     |
| <b>G46</b>           | Wholesale trade, except of motor vehicles and motorcycles                                                                                                                   |
| <b>G47</b>           | Retail trade, except of motor vehicles and motorcycles                                                                                                                      |
| <b>H</b>             | Transportation and storage                                                                                                                                                  |
| <b>I55</b>           | Accommodation                                                                                                                                                               |
| <b>J58-J60</b>       | Publishing activities; motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities  |
| <b>J61</b>           | Telecommunications                                                                                                                                                          |
| <b>J62-J63</b>       | Computer programming, consultancy and related activities; information service activities                                                                                    |
| <b>L68</b>           | Real estate activities                                                                                                                                                      |
| <b>M69-M71</b>       | Legal and accounting activities; activities of head offices and management consultancy activities; architectural and engineering activities; technical testing and analysis |
| <b>M72</b>           | Scientific research and development                                                                                                                                         |
| <b>M73-M75</b>       | Advertising and market research; other professional, scientific and technical activities; veterinary activities                                                             |
| <b>N77-N82_X_N79</b> | Administrative and support service activities, excluding travel agency, tour operator and other reservation service and related activities                                  |
| <b>N79</b>           | Travel agency, tour operator and other reservation service and related activities                                                                                           |
| <b>S951</b>          | Repair of computers and communication equipment                                                                                                                             |

### 7.2 Sectoral AI adoption across countries, 2025

The graph below displays AI adoption according to different sectors and countries. 33 European countries (EU27 plus Albania, Bosnia and Herzegovina, Montenegro, Serbia,

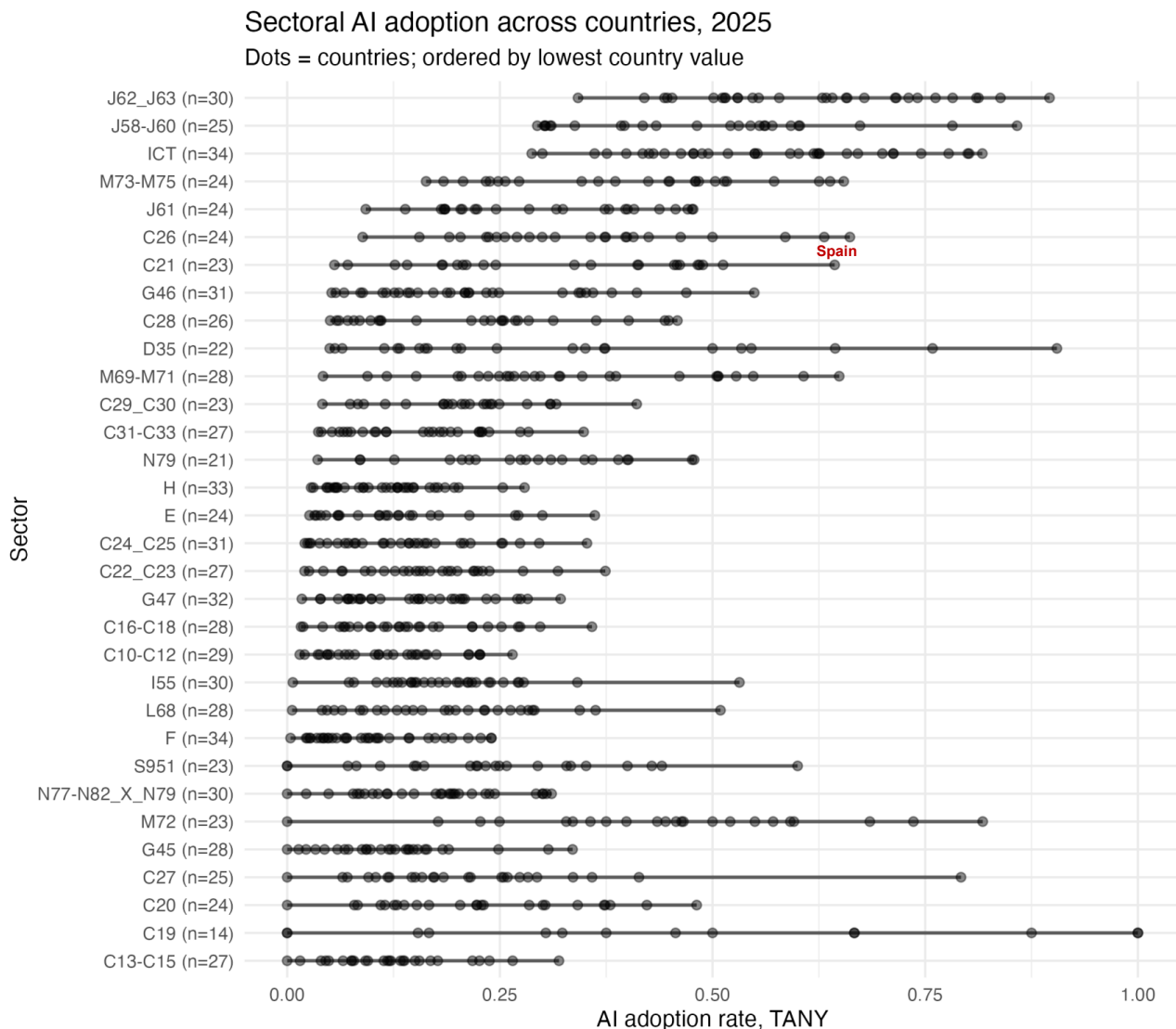
Turkey and Norway) were included, as well as 12 sectors. The *Manufacturing* sector (sector C) was further divided into its upper and lower band. Please check table in Annex 7.1 to know the names of the sector, corresponding to each NACE code. The results show that *ICT* and *professional, scientific and technical activities* (sector M) consistently ranked in the top 3 sectors with the highest AI adoption rate across all countries.



### 7.3 Sectoral AI adoption across countries, 2025

The graph below shows the results of a more granular sectoral analysis carried out on a sample of 33 European countries (EU27 plus Albania, Bosnia and Herzegovina, Montenegro, Serbia, Turkey and Norway) and 32 sectors. In the graph, each data point corresponds to a specific country. We decided to highlight Spain's high adoption rate in the pharmaceutical sector (NACE C21 in Eurostat) – a theme further explored on page 14, in the box **Focus: AI in Spain's pharmaceutical industry**. Other countries were not signalled

as we considered the results out of the scope of the research conducted here.



#### 7.4 Results from Italian companies

Evidence from a survey conducted by the Istituto Guglielmo Tagliacarne – the Study Centre of the Italian Union of Chambers of Commerce (Unioncamere)<sup>9</sup> – among a sample of 4,500 Italian firms with 5-499 employees provides an original perspective on how businesses are approaching the AI transition. The survey does not merely measure the diffusion of AI. It explores: (i) the type of tools adopted, (ii) their integration into existing and new activities, (iii) the benefits and risks perceived by firms, (iv) the expected consequences for employment.

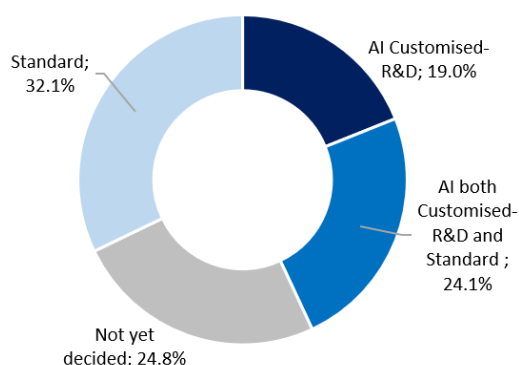
<sup>9</sup> Istituto Guglielmo Tagliacarne is the research body of Unioncamere, providing studies and socio-economic analysis for and in cooperation with the Italian Chambers' System, and with Ministries and other institutions. It is part of the National Statistical System with projects on territorial economic accounting included in the national official statistics. It has a multidisciplinary research team (statistics, econometrics, and policy analysis), managing quantitative and qualitative analysis at desk and field level.

AI use is already significant but far from universal. In Italy, 16.1% of firms currently use AI tools on a stable basis, while another 33.2% plan to start using them within the next three years (Figure 1). Overall, almost half of Italian firms (49.3%) expect to use AI by 2029.

However, this diffusion is uneven. By 2029, 63.2% of medium-sized and large firms (50-499 employees) are expected to use AI, compared with 44.8% of smaller firms (5-49 employees). This is consistent with European evidence showing that AI adoption rises with firm size, while SMEs continue to lag behind<sup>10</sup>.

Moreover, the survey shows that AI is entering Italian businesses through different paths. Around one-third (32.1%) of current or prospective adopters use standardised tools already available on the market. By contrast, 19% use customised solutions developed through research and development, while 24.1% combine standard and customised applications. A further 24.8% have not yet identified which type of solution they intend to implement.

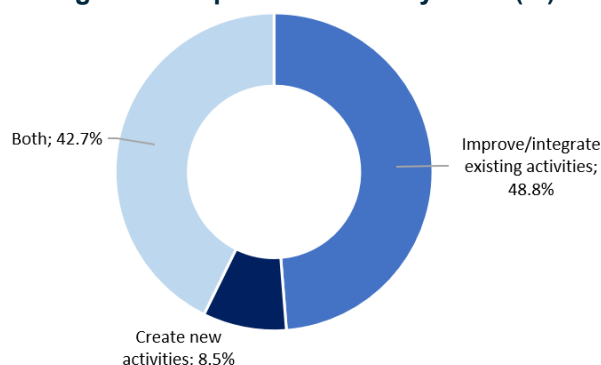
**Figure 1. Types of AI tools used by firms (%)**



Source: Istituto Guglielmo Tagliacarne-Unioncamere survey

Beyond the type of tool adopted, it is equally important to understand how AI is integrated into business processes. Among firms that already invest or plan to invest in that technology, 48.8% use it mainly to improve or complement existing activities. Only 8.5% use it exclusively to develop entirely new activities, while a substantial 42.7% combine the improvement of current processes with the creation of new ones (Figure 2).

**Figure 2. Purpose of AI use by firms (%)**



Source: Istituto Guglielmo Tagliacarne-Unioncamere survey

<sup>10</sup> Eurostat (2026), *Use of artificial intelligence in enterprises*, Statistics Explained, 2 June 2026, European Commission.

Taken together, these two dimensions – the type of AI solution and the way it is embedded in business processes – point to different levels of technological and organisational maturity. This interpretation is consistent with recent European Commission evidence showing that AI adoption is not a purely technical process, but often requires firms to redesign workflows, reallocate tasks, retrain workers and adapt organisational structures. Where these adjustment costs are higher, firms may delay adoption or implement AI in less transformative ways<sup>11</sup>.

As the European Central Bank highlights, productivity gains from AI require technological readiness, investment and organisational change<sup>12</sup>. Its strategic potential emerges when firms move beyond efficiency gains to redesign processes, develop new services and strengthen decision-making.

The econometric analysis (which includes structural controls such as size, sector, and geographical location) shows that firms using customised or combined AI solutions are 5.1 percentage points more likely to expect an increase in turnover than firms relying solely on standardised tools (Table 1, Model A). The estimated effect is statistically significant.

**Table 1. Effect of the type of AI tools used on firms' expectations of turnover growth**

**Dependent variable:** expected turnover growth (*dummy variable equal to 1 if the firm expects its turnover to increase, and 0 otherwise*)

|                                 | Entire sample<br>(A) | Subsample by size class |                     |
|---------------------------------|----------------------|-------------------------|---------------------|
|                                 |                      | Micro-small<br>(B)      | Medium-large<br>(C) |
| AI tool type                    |                      |                         |                     |
| 0. No AI use                    | -0.104***<br>(0.023) | -0.102***<br>(0.025)    | -0.118**<br>(0.052) |
| 1. AI Standard (reference cat.) |                      |                         |                     |
| 2. AI Customised                | 0.051*<br>(0.028)    | 0.060*<br>(0.031)       | 0.028<br>(0.060)    |
| + controls                      |                      |                         |                     |
| Obs                             | 4,204                | 3,411                   | 793                 |
| LR chi2                         | 199.4***             | 130.60***               | 33.20**             |
| Pseudo R2                       | 0.040                | 0.033                   | 0.032               |

The full sample excludes firms that selected "Not yet decided." The variable "2. AI Customised" includes: "AI Customised-R&D" and "AI both Customised-R&D and Standard" related to the Figure 3. Controls: size (micro, small, medium, large), industry (14 industries Nace Rev.2), geographical location (North-West, North-East, Center, South). The table displays average marginal effects. Standard errors in parentheses. Likelihood ratio (LR) chi-square testing the joint significance of the explanatory variables. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

Source: Elaboration by Istituto Guglielmo Tagliacarne-Unioncamere

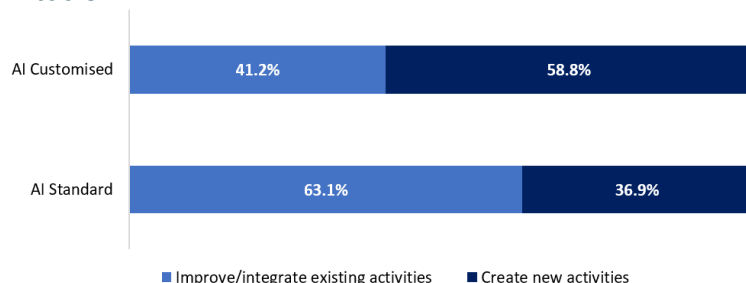
One possible transmission channel behind this relationship between personalized tools and turnover growth expectations is the more transformative use enabled by customisation. Among firms using customised or combined solutions, 58.8% use AI to develop new activities, either alone or alongside the improvement of existing ones, compared with 36.9%

<sup>11</sup> Canton, E. (2026). *Labour market institutions and the adoption of artificial intelligence: Evidence on workforce adjustment and technology diffusion across firms*. Research and Innovation Paper series, Directorate-General for Research and Innovation, Publications Office of the European Union.

<sup>12</sup> Bergeaud, A., González-Torres Fernández, G., Labhard, V., & Sellner, R. (2025, March 28). *AI can boost productivity – if firms use it*. The ECB Blog, European Central Bank.

of firms relying on standard applications. By contrast, 63.1% of firms using standard applications rely on AI only to improve or integrate existing activities, compared with 41.2% of firms using customised or combined solutions (Figure 4).

**Figure 4. Share of firms by purpose of AI use: users of customised AI tools versus users of standard AI tools**



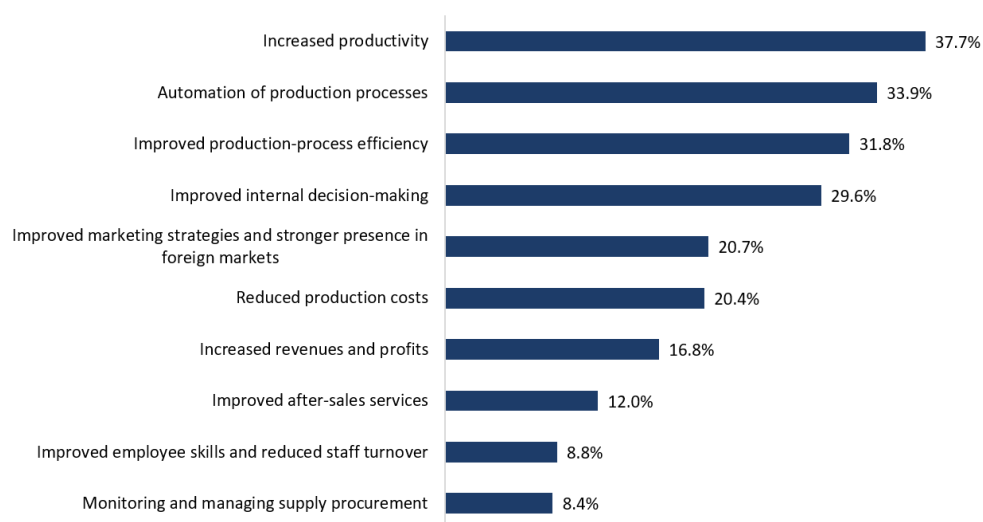
The variable “AI Customised” includes: “AI Customised-R&D” and “AI both Customised-R&D and Standard” related to the Figure 3. The variable “Create new activities” includes: “Create new activities” and “Both” related to Figure 2.

Source: Istituto Guglielmo Tagliacarne-Unioncamere survey

The way firms adopt and integrate AI also shapes the benefits they expect to obtain and the risks they associate with its use. The survey therefore helps to identify not only how widely AI is spreading, but also the main channels through which businesses expect it to affect their performance and organisation.

The benefits identified by Italian businesses are strongly connected with competitiveness. Higher productivity is the most frequently cited advantage, reported by 37.7% of firms. It is followed by process automation at 33.9%, greater production efficiency at 31.8% and improved internal decision-making at 29.6% (Figure 5). Around one-fifth also expect AI to strengthen marketing and international market presence (20.7%) or reduce production costs (20.4%). These expectations are coherent with the results in this Working paper, which find a positive relationship between AI adoption and labour productivity.

**Figure 5. Main benefits of AI adoption reported by firms (% , multiple responses)**

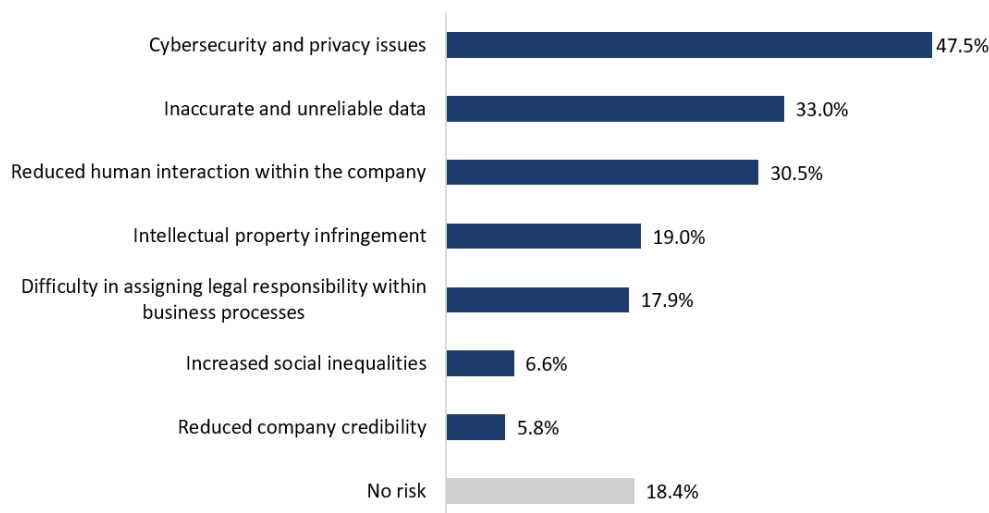


Source: Istituto Guglielmo Tagliacarne-Unioncamere survey

Firms are nevertheless highly conscious of the associated risks. More than four out of five identify at least one concern. Cybersecurity and privacy rank first, at 47.5%, followed by

inaccurate or unreliable information at 33%, and the weakening of human relationships within the firm at 30.5% (Figure 6). Intellectual-property violations and unclear legal responsibilities are also relevant concerns.

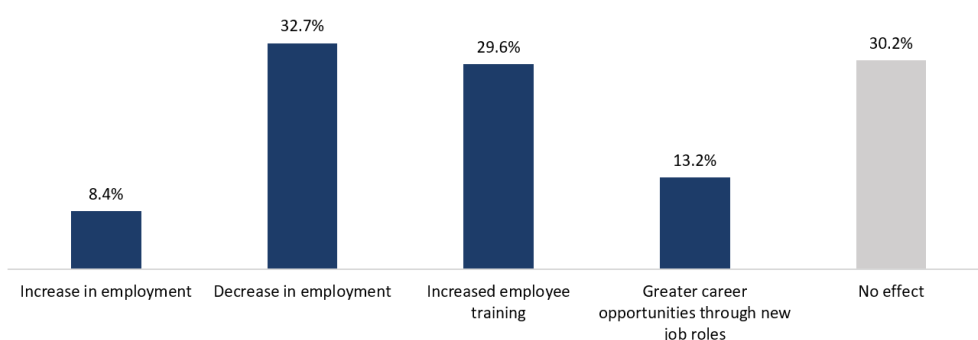
**Figure 6. Main risks of AI adoption reported by firms (% , multiple responses)**



Source: Istituto Guglielmo Tagliacarne-Unioncamere survey

The labour-market implications are more ambiguous: 32.7% of surveyed firms expect AI to reduce employment, while only 8.4% anticipate a direct increase. However, 29.6% expect greater investment in worker training, 13.2% foresee improved career opportunities, and 30.2% expect no overall employment effect (Figure 7). As the answers are not mutually exclusive, firms may simultaneously anticipate some task displacement and stronger demand for new skills.

**Figure 7. Firms' perceptions of the effects of AI on employment (%)**



Source: Istituto Guglielmo Tagliacarne-Unioncamere survey

The Italian results suggest why a clear aggregate effect is difficult to identify: AI may substitute some tasks, complement others and change the composition of skills before materially affecting total employment. Indeed, as highlighted by OECD<sup>13</sup>, the impact of AI depends heavily on how firms redesign jobs and involve workers in the adoption process.

<sup>13</sup> Lane, M., Williams, M., & Broecke, S. (2023). *The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers* (OECD Social, Employment and Migration Working Papers No. 288). OECD Publishing.



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